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Multinationals, robots and the labor share

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Abstract
Using a panel of Spanish manufacturing firms covering the 1990-2017 period, this paper shows that firms acquired by multinational enterprises experience a reduction in the labor share. Acquisitions drive significant changes in the production process of affiliates. One of the key aspects of this reorganization is the systematic adoption of robots, which allow affiliates to scale up production and expand into foreign markets but reallocate income away from labour. The results are supported by a model of automation choices with heterogeneous firms and are robust to accounting for selection into multinational ownership and robot adoption. Counterfactual results indicate that, in the absence of multinationals and robots, the manufacturing labor share would be at its level of two decades ago. These findings shed new light on how globalization and technological change jointly contribute to the decline in the labor share.

Key words: multinational enterprises, industrial robots, labor share, globalization, technological change
JEL: F23; F66; O33

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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 (Alfaro, Chanda, Kalemli-Ozcan and Sayek, 2010; Harrison and Rodríguez-Clare, 2010). Affiliates of MNEs in fact 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 (Doraszelski and Jaumandreu, 2018), MNEs 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 article, 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 (Acemoglu and Restrepo, 2018). 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 ownership. 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) may interact and reinforce each other in driving the downward trend.

I establish these results using the Survey on Business Strategies (ESEE), a representative panel of Spanish manufacturing firms covering the 1990-2017 period, which contains rich details about firms' production and organizational choices. Crucially for this paper, the ESEE also reports information about ownership and robot adoption. To supplement the data at the firm level, I create a new cross-country industry-level panel about multinational production, labor share, and robots 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 at most once from domestic to multinational ownership, that is, they become multinational

[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.

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 are more involved in international trade than domestic firms. This is a well-known fact in the literature (Antràs and Yeaple, 2014), and helps to explain the interest that policymakers have in MNEs.

I use the data to document two new facts. First, multinational affiliates have a lower labor share (defined as the ratio between the wage bill and variable production costs) than domestic firms. Decomposing the labor share into within-group and between-group components reveals that the decline within the group of multinational affiliates accounts for approximately 75% of the overall reduction, indicating that changes among these firms are key to understanding labor share dynamics at the industry level. Second, multinational affiliates consistently exhibit a higher rate of robot adoption than domestic firms. Both facts hold conditional on firm size. Using the cross-country industry-level data, I show that analogous patterns also apply beyond the Spanish manufacturing sector.

I introduce a model of robot adoption with heterogeneous firms consistent with these facts. As in the workhorse of Acemoglu and Restrepo (2018), firms carry out a unit measure of tasks to produce output. Tasks below a certain threshold can be performed by material inputs or labor, whereas tasks above it can only be performed by labor. Under the standard assumption that labor has a comparative advantage in higher-indexed tasks, there is perfect specialization in equilibrium, with material inputs used in tasks below the threshold and labor in those above. Robot adoption shifts this threshold rightward, reducing marginal costs and reallocating income away from labor. Unlike Acemoglu and Restrepo (2018), investing in robots requires paying a sunk cost and firms differ along three dimensions: productivity, demand shocks, and the cost of adopting robots.

Through the lenses of the model, multinational affiliates may have higher incentives than domestic firms to adopt robots, and therefore a lower labor share, because they are more productive (e.g., thanks to better management, as in Bloom et al., 2012), face higher demand (e.g., due to better marketing or increased trade within the firm, as in Arnold and Javorcik, 2009; Guadalupe, Kuzmina and Thomas, 2012), or have lower adoption costs (e.g., because of lower financial and information frictions, as in Harrison and McMillan, 2003; Desai, Foley and Hines Jr, 2004; Keller and Yeaple, 2013; Manova, Wei and Zhang, 2015).

The richness of the ESEE survey allows me to test these hypotheses. To do so, I estimate firm-level event-study specifications in which I regress the outcome of interest on a binary variable indicating the years before or after the relevant treatment, which can be either a multinational acquisition or robot adoption, as well as firm and year-level fixed effects. The identification assumption is that not-yet and never treated firms are a credible counterfactual for treated ones after controlling for firm-level time-invariant heterogeneity and time-varying shocks common to all firms. Because both treatments take place in different years and their effects may change over time, I use the method proposed by Sun and Abraham (2021) to identify the coefficients of interest.[2]

The estimates reveal that acquired firms experience an average labor share reduction of about 6 percentage points (10% relative to the sample average), and support the hypothesis that investment in robots contributes to this decline.[3] After the acquisition, firms increase the probability of adopting robots by about 17 percentage points (89% relative to the sample average). In turn, robot adoption decreases the labor share by about 2 percentage points, one-third of the overall reduction following multinational acquisitions.

Next, I inspect the channels through which multinational acquisitions contribute to increased investment in robots. To evaluate if multinational ownership makes firms more productive, I inspect the change in affiliates' value added in production following the acquisition. To assess if multinational acquisitions boost firm-level demand, I use a survey question asking firms whether their parents grant them access to export markets.[4] Finally, to determine the importance of adoption costs, I analyze whether multinational parents favor affiliates' investment by relaxing their credit constraints or transferring technological knowledge to them. The estimates reveal that acquired firms experience a productivity increase of about 25%. Additionally, conditional on exporting, multinational affiliates are about 36 percentage points more likely to serve foreign markets through their parental network than any other channel, and their export sales increase. There is no evidence that acquired firms face lower adoption costs. Among all potential channels examined, increased foreign market access through the parental network has the strongest explanatory power for robot adoption.

Multinational acquisitions also induce other changes in production process. For instance, there is evidence that affiliates shift from small-scale production to 24/7 operations, which may necessitate an automated production pipeline, and adopt complementary technology to robots (e.g., CAD manufacturing). Notably, I show that these other investments do not predict a reduction in the labor share, emphasizing the fact that robots play

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

[3]I discuss alternative mechanisms proposed in the literature in Section 4.2.

[4]The survey asks firms if they access export markets via their parents (either using their distribution channel or directly selling to them) or via other means (e.g., specialized intermediaries or own means).

a key role in explaining the observed decline within affiliates.

Although suggestive of a causal relationship, one concern is that non-random selection into multinational ownership and robot adoption may bias the estimates. Absent firm-level experimental variation, I combine the event-study design with a matching estimator (a common approach in the literature, e.g., Arnold and Javorcik, 2009; Guadalupe et al., 2012; Koch, Manuylov and Smolka, 2021). I proceed in two steps. First, I match each treated firm to the most similar five untreated ones in terms of observable characteristics in trends (to account for differences in growth) and levels (to account for differences in size, productivity, openness to trade, innovation, and capital intensity) prior to the relevant event (multinational acquisition or robot adoption). In the second step, I estimate the event-study regressions on the matched sample. All the results discussed are robust to this approach, which strengthens their interpretation.

Finally, I use the reduced-form estimates to examine how changes at the firm level shape industry-level labor share dynamics. I consider two counterfactual scenarios. In the first, I simulate how the Spanish manufacturing labor share would have evolved in the absence of MNEs over the sample period. In the second, I simultaneously turn off the contribution of multinational ownership and robot adoption. In each scenario, I roll forward the event-study equations using the estimated parameters to construct counterfactual firm-level labor share paths, which I then aggregate at the industry level using firms' observed employment shares as weights. The results suggest that, in the absence of multinationals and robots, the counterfactual labor share at the end of the sample period would equal its observed level of two decades earlier. Robot adoption induced by multinational acquisitions explains about one-fifth of this increase. 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 et al., 2004; Manova et al., 2015), innovate more (Guadalupe et al., 2012), trade more (Hanson, Mataloni Jr and Slaughter, 2005; Ekholm, Forslid and Markusen, 2007; Ramondo, Rappoport and Ruhl, 2016; Conconi, Leone, Magerman and Thomas, 2022), 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, 2021), Spain (Koch et al., 2021), and Denmark (Humlum, 2021) shows that robot adopters tend to be large manufacturing firms often involved in international trade. By showing that multinational ownership spurs 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 in many economies. 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),[5] 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) may interact and reinforce each other in driving down the labor share.

The paper unfolds as follows. Section 2 introduces the data. Section 3 presents the motivating facts. Section 4 contains the model. Section 5 reports the empirical results. Section 6 discusses the counterfactuals. Section 7 concludes.

[5]A key difference between this paper and Stapleton and Webb (2022), who also use the ESEE data to study firms' 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). While our papers are complementary, focus and conclusions differ.

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, the SEPI Foundation has surveyed about 1,800 firms each year and made an effort to minimize the sample deterioration due to either firms' 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 firms' 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 firms' 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.[6] 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 (outward FDI).[7] Lastly, I exclude firms involved in domestic mergers during the sample period. The final sample includes domestic-owned firms and those switching once from domestic to multinational ownership after 1991.

[6] The ESEE data do not report if a firm is owned by a Spanish multinational. Nevertheless, I expect the conclusions of this paper to hold for these acquisitions as well.

[7] 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.

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) in manufacturing activity". Based on the response to this question, I create a binary indicator that equals 1 if a firm uses "Robotics" (system 2) in a given year and 0 otherwise.[8] 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 for the other types of technology following the same rule.

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 total 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 acquired by a multinational. Table B.1 reports the number of acquisitions by year. Table B.2 shows summary statistics by ownership pooling together pre and post-acquisition periods for multinational affiliates (sample variables are defined in Table B.3). Firms acquired by multinationals 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 C.1 shows that the same pattern holds when comparing domestic firms with affiliates before the acquisition (i.e., excluding the post-acquisition periods). Multinational affiliates have an average lower labor share than domestic ones (57% versus 63%). About 45% of multinational affiliates and 23% of domestic firms adopt robots during the sample period.

Although multinational affiliates represent only about 3% of the total, they account for about 23% of production, 25% of exports, 15% of employment, and 30% of capital stock in the Spanish manufacturing sector. The fact that multinational affiliates are a small share of the population and yet account for a disproportionally large amount of

[8] Although industrial robots are not explicitly mentioned, 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).

economic activity is consistent with the literature. Antràs, Fadeev, Fort and Tintelnot (2022) document that multinationals in the US are less than 1% of firms but account for 42% of manufacturing employment and over 70% of imports and exports. Arnold and Javorcik (2009), Bircan (2019), and Conconi et al. (2022), report similar figures for Indonesia, Turkey, and Belgium, respectively.

2.2 Industry-Level Data

I create a new cross-country industry-level dataset with information about multinational production, labor share, and industrial robots. Data about multinational production come from the Analytical Multinational Enterprises Database (AMNE) of the Organization for Economic Cooperation and Development (OECD). This database provides a breakdown of gross output by domestic and multinational firms at the country-industry-year level.

Information about the national share of income accruing to labor comes from the Socio-Economic Account (SEA) database of the World Input-Output Database (WIOD). These data also contain standard industry accounts (e.g., employment, wages, fixed assets, exchange rates, and price deflators). Data on industrial robots come from the International Federation of Robotics (IFR), the most widely used source for robot adoption studies (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020). The IFR aggregates cross-country firm-level information and reports the stock of industrial robots at the country-industry-year level.

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 B.4 shows sample summary statistics.

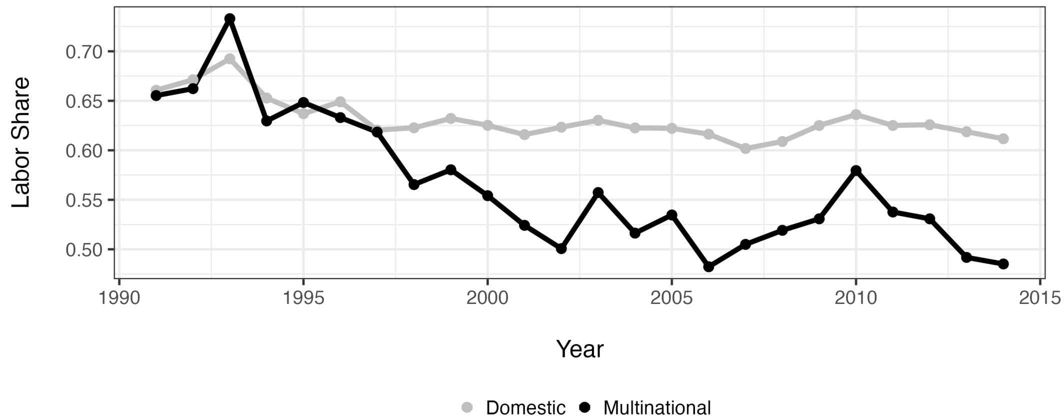
3 Motivating Facts

This section presents two new facts about multinational affiliates, their labor share, and robot adoption choices motivating this paper.

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

Figure 1 shows that the labor share declines during the sample period. However, while domestic firms experience a modest total decrease (from 66% to 61%), multinational affiliates witness a sharper reduction (from 65% to 48%) and systematically exhibit a lower labor share. Figure C.2 shows that a similar pattern holds conditional on firm size. It is useful to benchmark these trends against the industry-level manufacturing labor share

Figure 1. Labor Share by Ownership



Note: The Figure shows the labor share trends among domestic firms and multinational affiliates. While the labor share declines within both groups, multinational affiliates experience a sharper reduction and exhibit a lower labor in levels.

change to understand their magnitude. Building upon Olley and Pakes (1996), I express yearly changes in the industry-level labor share as follows:

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

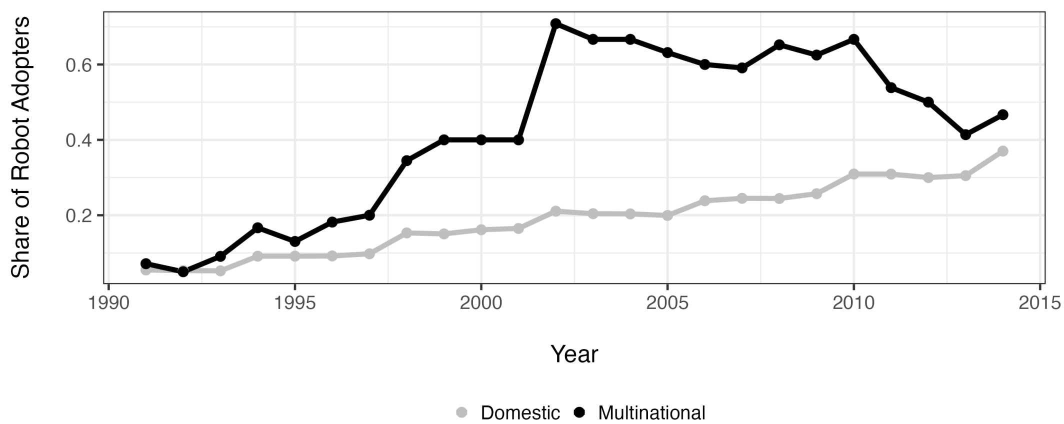
Changes in the labor share can be attributed to the sum of changes in the unweighted mean of the labor share ($\overline{ls}_t$), which reflects within-group dynamics, and changes in the covariance between the market share of each group (s_{it}) and its labor share (ls_{it}), which capture between-group reallocation. Figure C.3 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.[9]

Fact 2. *Multinational affiliates are more likely to adopt robots than domestic firms.*

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. Figure C.4 shows that this pattern holds conditional on firm size. Figure C.5 shows a similar cross-sectional pattern across industries. Because multinational affiliates represent

[9]Among MNEs, 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

Figure 2. Share of Robot Adopters by Ownership



Note: The Figure shows the share of robot adopters among domestic firms and multinational affiliates. While adoption rates increase within both groups, multinational affiliates experience a sharper increase and exhibit a higher adoption rate in levels.

about 3% of total firms in each year, Figure 2 does not merely reflect changes in sample composition.

Beyond Spanish Manufacturing. Using the cross-country industry-level panel, Figure C.6 shows that (the log of) multinational production negatively correlates with the labor share (left panel) and positively correlates with (the log of) the number of robots per thousand employees (right panel), a standard measure of robots' diffusion (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020). Table B.5 shows that these correlations are significant and robust to controlling for capital and labor prices and employment levels as well as country-by-industry and year-level fixed effects. This evidence suggests that Facts 1 and 2 are general trends that apply beyond Spanish manufacturing.

4 Theoretical Framework

This section introduces a simple model consistent with Facts 1 and 2. The model delivers testable predictions about the relationship between multinational ownership, labor share, and robot adoption. Derivations can be found in Appendix D (Section D.2).

between the 1990s and 2000s is due to market share reallocation to "superstar firms" with low labor share. See Appendix D (Section D.1).

4.1 Model

The Environment. There is a large number of heterogeneous 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. Second, firms produce and sell output. For simplicity, I assume that firms invest in robots only once and, if they do, they keep robots forever.[10]

Production Technology. Production requires carrying out a unit measure of tasks ω. Firms' production function is:

$$Y_{ft} = z_{ft} \left(\int_0^1 y_{ft}(\omega)^{\frac{\sigma-1}{\sigma}} d\omega \right)^{\frac{\sigma}{\sigma-1}}, \quad \sigma > 1. \tag{2}$$

z_{ft} denotes Hicks-neutral productivity. $y_{ft}(\omega)$ is the output of each task, and σ is the elasticity of substitution between tasks. Each task is produced as:

$$y_{ft}(\omega) = \mathbf{1}\{\omega \leq \bar{\omega}_{ft}(R_{ft})\}\gamma_{ft}(\omega)M_{ft}(\omega) + \phi_{ft}(\omega)L_{ft}(\omega). \tag{3}$$

R_{ft} is a binary variable equal to 1 if firm f employs robots at time t. $M_{ft}(\omega)$ and $L_{ft}(\omega)$ are the quantity of material inputs and labor employed in each task, and $\gamma_{ft}(\omega)$ and $\phi_{ft}(\omega)$ are their productivity levels. Equation (2) states that inputs are perfect substitutes in any task $\omega \leq \bar{\omega}(R_{ft})$. However, only labor can perform tasks $\omega > \bar{\omega}(R_{ft})$. I introduce two standard assumptions.

Assumption 1. $\phi_{ft}(\omega)/\gamma_{ft}(\omega)$ is strictly increasing in ω and $w_t/\phi_{ft}(\bar{\omega}_{ft}) > r_t/\gamma_{ft}(\bar{\omega}_t)$.

Assumption 2. $\bar{\omega}_{ft}(1) > \bar{\omega}_{ft}(0)$.

Assumption 1 states that labor has a strict comparative advantage in tasks indexed by a higher ω. This assumption ensures that there exists a unique $\bar{\omega}_{ft}(R_{ft})$. Tasks below this threshold are carried out by material inputs, whereas tasks above it are performed by labor. Assumption 2 states that robot adoption reduces the set of tasks performed by labor. Firms' unit production costs can be expressed as:

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

[10]This assumption is consistent with the binary robot adoption indicator that I introduce in Section 2 and use in the empirical sections of the paper.

where $\alpha_{ft} = \int_0^{\bar{\omega}_{ft}(R_{ft})} \gamma_{ft}(\omega)^{\sigma-1} d\omega$ and $\beta_{ft} = \int_{\bar{\omega}_{ft}(R_{ft})}^1 \phi_{ft}(\omega)^{\sigma-1} d\omega$. Under Assumptions 1 and 2, robot adoption reduces marginal costs.

Demand and Market Structure. Each firm produces a single variety and faces a downard-sloped 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:

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

Their revenues can be expressed as:

$$\tilde{\pi}_{ft}(R_{ft}) = \Omega_t \psi_{ft} c_{ft}(R_{ft})^{1-\theta}, \tag{6}$$

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

Robot Adoption. Firms pay the sunk cost of robot adoption at time t if and only if the expected discounted profit stream they earn by undergoing the investment exceeds what they garner otherwise:

$$R_{ft} = 1 \iff \sum_{s=t}^{\infty} \beta^{s-t} \mathbb{E}_t \left[\tilde{\pi}_{ft}(1) \right] - FC_{ft} \geq \sum_{s=t}^{\infty} \beta^{s-t} \mathbb{E}_t \left[\tilde{\pi}_{ft}(0) \right]. \tag{7}$$

Firms have rational expectations over z_{ft} and ψ_{ft}. $\beta \in (0, 1)$ is the discount rate. FC_{ft} is the cost that firm f must pay when adopting robots at time t.

4.2 Model Predictions

Testable Hypotheses. The model delivers two predictions. First, investing in robots reduces firms' labor share. Second, firms with higher productivity (z_{ft}), higher demand shocks (ψ_{ft}), or lower adoption costs (FC_{ft}), are more likely to adopt robots.

The first prediction is standard in models based on Acemoglu and Restrepo (2018). The second prediction is based on the fact that investment in robots requires paying a sunk cost but reduces marginal production costs. As in models of heterogeneous firms based on Melitz (2003), firms with superior performance are more likely to undertake it. A similar prediction can be found in Bonfiglioli et al. (2021), Humlum (2021), and Koch et al. (2021). However, differently from previous literature, the model also allows for two additional channels, demand shocks and adoption costs, that the richness of the ESEE data allows me to disentangle from productivity.

Inspired by Figures 1 and 2, this paper emphasizes multinational ownership as a source of differences between firms. Therefore, I introduce the following hypotheses, which I test in the next section:

Hypothesis 1. *Multinational affiliates have a lower labor share than domestic firms, and this is partly due to robot adoption.*

Hypothesis 2. *Multinational affiliates are more likely to adopt robots than domestic firms because they are more productive, face higher demand, or have lower adoption costs.*

Discussion about Hypotheses. Aside from the adoption of robots, the literature suggests various alternative explanations for the decline in labor share. These include 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 (Böckerman and Maliranta, 2012; Panon, 2022), and market concentration (De Loecker, Eeckhout and Unger, 2020; Autor et al., 2020; Barkai, 2020; Azar and Vives, 2021). A survey of these explanations can be found in Grossman and Oberfield (2022).

The model presented in this section intentionally abstracts from these alternative mechanisms to focus on robot adoption, which is a novel channel in the literature about multinational enterprises. It should be noted that my results are consistent with the other above-mentioned channels to the extent that robot adoption induced by multinational acquisitions is complementary to them.

5 Empirical Analysis

This section provides evidence in favor of Hypotheses 1 and 2. The results are robust to accounting for selection into multinational ownership and robot adoption.

5.1 Empirical Strategy

Overall Approach. I test Hypothesis 1 in three steps. In the first step, I test if firms reduce their labor share after being acquired by a multinational. Next, to assess if robot adoption is one of the potential channels at play, I test whether multinational acquisitions spur robot adoption (step 2) and whether robot adoption reduces firms' labor share (step 3). I test Hypothesis 2 in two steps. First, I check if acquired firms become more productive, face higher demand, or lower adoption costs. Second, I evaluate the explanatory power of each channel in determining the adoption of robots.

Empirical Implementation. I estimate the following equation:

$$y_{ft} = \sum_{s=-\underline{k}}^{\bar{k}} \beta_s D_{ft}^s + \alpha_f + \alpha_t + \varepsilon_{ft}. \tag{8}$$

y_{ft} represents the outcome of firm f in year t. D_{ft}^s is a binary variable that identifies the years before or after the relevant treatment, which can be either a multinational acquisition or robot adoption, depending on the specification being considered. $\underline{k}$ and $\bar{k}$ denote the first and last period for which D_{ft}^s can be defined. α_f and α_t are firm and year-level fixed effects, respectively. The coefficients β_s measure the dynamic treatment effects. I normalize $\beta_{-1} = 0$. Therefore, the estimated coefficients are relative to the year before the treatment. I cluster standard errors at the firm level. I estimate equation (8) using all firms in the sample. The β_s coefficients are identified from within-firm variation under the (parallel trends) assumption that never treated and not-yet-treated firms are a credible counterfactual for treated ones, conditional on the fixed effects.

Several papers show that estimating event studies with a two-way fixed-effects (TWFE) estimator may fail to recover the treatment effect when the roll-out is staggered and treatment effects evolve over time.[11] The problem arises because already treated units enter the control group for some cohorts, generating a "forbidden comparison" (Borusyak et al., 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. Appendix E shows that the results are qualitatively robust to using a TWFE estimator.

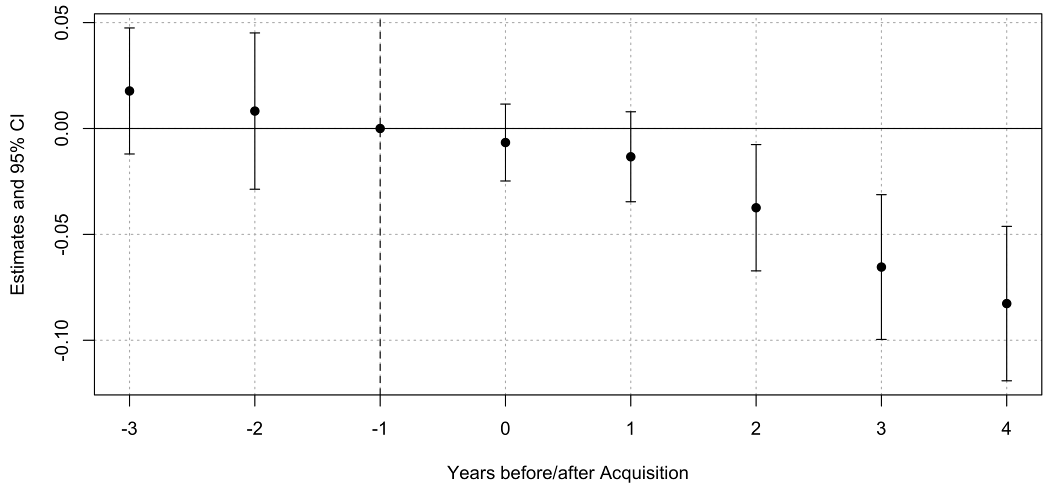
5.2 Testing Hypothesis 1

Multinationals and the Labor Share. I estimate equation (8) with the labor share as the outcome variable. The independent variables are the leads and lags of a binary indicator equal to 1 if firm f is owned by a multinational at time t and 0 otherwise. Figure

[11] See, e.g., De Chaisemartin and d'Haultfoeuille (2020), Sun and Abraham (2021), Borusyak, Jaravel and Spiess (2021), Callaway and Sant'Anna (2021), Goodman-Bacon (2021).

3 shows that the labor share decreases following multinational acquisitions. The average

Figure 3. Multinationals and the Labor Share



Note: The Figure plots the estimates I obtain from equation (8) using the labor share as the dependent variable and the leads and lags of a binary indicator equal to 1 if firm f is owned by a multinational at time t as the independent variable. The unit of observation is a firm-year pair. There are 24,106 observations. I cluster standard errors at the firm level. I report the estimates for $[\underline{k}, \bar{k}] = [-3, 4]$.

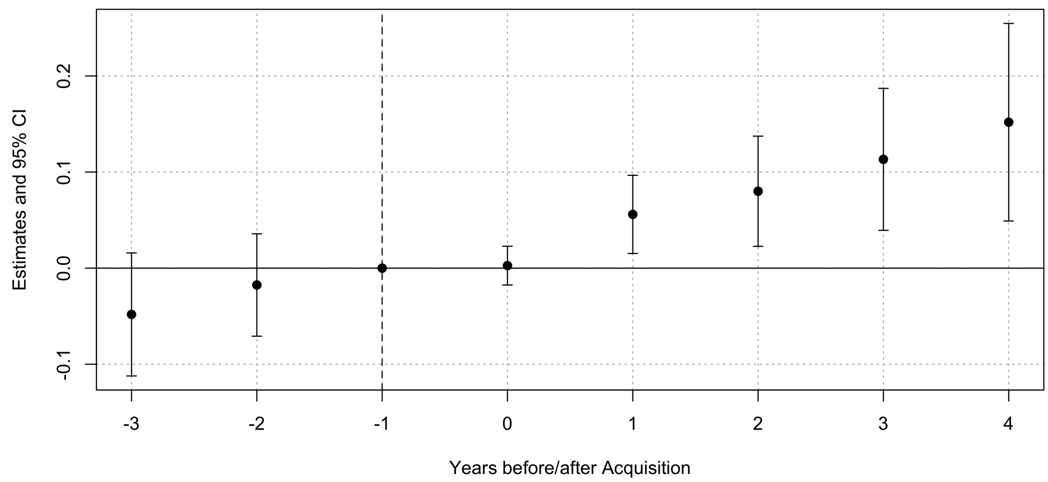
reduction across all cohorts and post-acquisition periods is approximately 6 percentage points, corresponding to a 10% reduction relative to the sample average labor share. Figure C.7 shows that results are robust to including industry-by-year fixed effects to account for common shocks to all firms in a two-digit industry.

Figure C.8 decomposes the labor share into its components: (the log of) intermediate inputs, labor costs, and the number of employees. Although acquired firms experience an increase in labor costs (3%) and employment (12%), the expenditure on intermediate inputs rises disproportionately (39%), leading to a decrease in the labor share. This finding aligns with existing literature documenting that multinational acquisitions can redistribute income across production factors within affiliates (Koch and Smolka, 2019) while boosting overall firm-level labor demand and wages (Almeida, 2007).

Despite being statistically insignificant and small in magnitude, Figure 3 features pre-trends going in the same direction as the treatment effect, raising potential concerns about the validity of the parallel trends assumption. In Section 5.5, I show that the results are robust to accounting for selection into multinational ownership.

Multinationals and Robot Adoption. I estimate the same equation as used in Figure 3, but with a binary indicator equal to 1 since the first year firm f adopts a robot as the outcome variable. Figure 4 shows that the probability of adopting robots increases after the acquisition. The average increase across all cohorts and post-acquisition periods is

Figure 4. MULTINATIONALS AND ROBOT ADOPTION

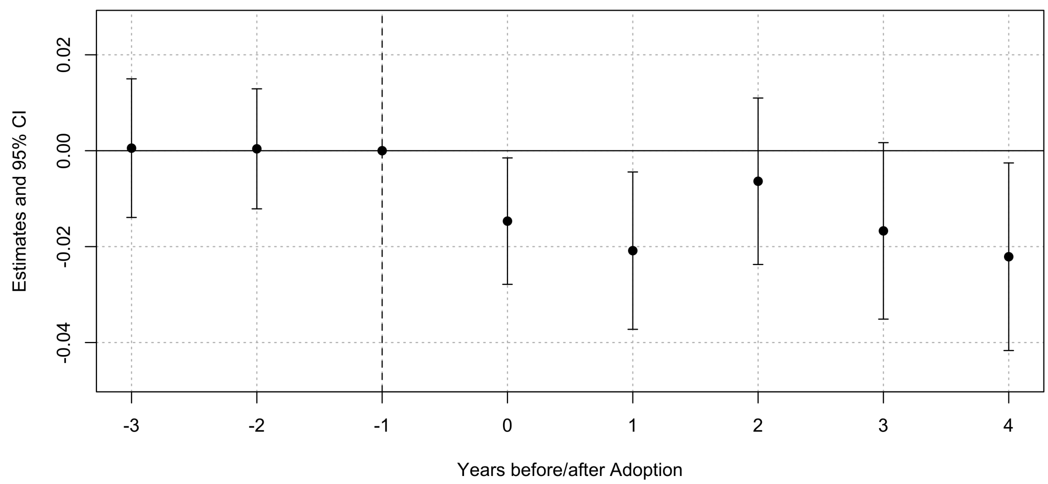


Note: The Figure plots the estimates I obtain from equation (8) using a binary indicator equal to 1 since the first year firm f adopts a robot as the outcome variable and the leads and lags of a binary indicator equal to 1 if firm f is owned by a multinational at time t as the independent variable. The unit of observation is a firm-year pair. There are 24,106 observations. I cluster standard errors at the firm level. I report the estimates for $[\underline{k}, \bar{k}] = [-3, 4]$.

about 17 percentage points, corresponding to a 89% increase relative to the unconditional probability of employing robots in the sample. Figure C.9 shows that the results are robust to including industry-by-year fixed effects. As in Figure 3, pre-trends going in the same direction as the treatment effect raise potential concerns about the validity of the parallel trends assumption, which are formally addressed in Section 5.5.

Robot Adoption and the Labor Share. I estimate equation (8) with the labor share as the outcome variable. The independent variables are the leads and lags of a binary indicator equal to 1 since the first year firm f adopts a robot. Figure 5 shows that the labor share decreases after the adoption event. The average reduction across all cohorts and post-adoption periods is about 2 percentage points, corresponding to a 3% reduction relative to the sample average labor share. This number represents one-third of the overall reduction in Figure 3. Figure C.10 shows that the results are robust to including industry-by-year fixed effects.

Figure 5. Robot Adoption and the Labor Share



Note: The Figure plots the estimates I obtain from equation (8) using the labor share as the dependent variable and the leads and lags of a binary indicator equal to 1 since the first year firm f adopts a robot as the independent variable. The unit of observation is a firm-year pair. There are 24,096 observations. I cluster standard errors at the firm level. I report the estimates for $[\underline{k}, \bar{k}] = [-3, 4]$.

The lack pre-trends suggests that the labor shares of the two groups follow parallel trends before the adoption. Section 5.5 addresses potential remaining concerns about unobserved heterogeneity confounding the estimates. Altogether, Figures 3, 4, 5 provide evidence in support of Hypothesis 1.

5.3 Testing Hypothesis 2

Why do Multinationals Adopt Robots? The model posits that firms with higher productivity, larger demand, or lower investment costs are more inclined to adopt robots. Previous research suggests that multinational affiliation may serve as a catalyst for all these factors. 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 (Arnold and Javorcik, 2009; Guadalupe et al., 2012; Koch and Smolka, 2019; Conconi et al., 2022). 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 technological knowledge to them (Branstetter, Fisman and Foley, 2006; Keller and Yeaple, 2013; Bilir and Morales, 2020).

Multinational Acquisitions Boost Productivity and Market Access. 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.

To test the explanatory power of each hypothesis, I estimate equation (8) using these four variables as an outcome. Table B.6 shows the pooled estimates across all cohorts and post-acquisition periods. Column (1) shows that acquired firms experience an average productivity increase of about 25%. Column (2) shows that conditional on exporting, acquired firms are about 36 percentage points more likely to do it via their parental network than any other means. Table B.7 shows that export values also increase (Column 1), especially for acquired firms below the sample median in terms of sales (Column 2).[12] There is no evidence that affiliates increase external R&D per employee (Column 3) and imports of foreign technology (Column 4), which dismisses the investment cost channel.

Increased Market Access Boosts Robot Adoption. To evaluate the explanatory power of each channel for robot adoption, I regress the robot adoption indicator on the proxies for the mechanisms of interest, which I add progressively, and firm and year-level fixed effects.[13] Table B.8 shows the results. Whereas all variables positively correlate with robot adoption, only the ability to export via the parental network has statistically significant explanatory power. 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).

Tables B.6 and B.8 suggest 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

[12] I use a TWFE estimator to allow for heterogeneous treatment effects by size, which the Sun and Abraham (2021) estimator does not allow for.

[13] I use a TWFE estimator to include continuous and multiple binary indicators in the regression, which the Sun and Abraham (2021) estimator does not allow for.

to achieve this goal, but it reallocates income away from labor. These results support Hypothesis 2.[14]

5.4 Other Changes in the Production Process

Multinational acquisitions may also drive broader changes in the production process of affiliates and spur investment in other technology complementary to robots.[15] For instance, Table B.9 shows that acquired firms are about 12 percentage points less likely to perform batch manufacturing, i.e., small-scale serial production, and about 8 percentage points more likely to engage in continuous manufacturing, a 24/7 large-scale production activity which requires an automated production pipeline.

Next, 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 are automatic machines that execute specialized routine tasks. Whereas CAD manufacturing can be complementary to robots, flexible systems and numerically controlled machines should be understood as less versatile substitutes that cannot be reprogrammed to perform multiple tasks without human supervision. Table B.10 shows the pooled estimates I obtain from equation (8) using these indicators as outcomes. Upon acquisition, firms are about 9 percentage points more likely to employ CAD manufacturing and about 4 percentage points less likely to adopt any of the other two technologies.

Notably, Table B.11 shows that these changes in production process and investments in other technologies do not correlate with a reduction in the labor share.[16] If anything, there is evidence that some of them (e.g., CAD manufacturing) positively correlate with it. This suggests that not all changes induced by multinational acquisitions are labor-diminishing, and emphasizes the role of robots in explaining the labor share decline observed within firms after the acquisition. The finding that robots produce different labor

[14] In an earlier draft, I documented the importance of increased market access through the parental network for robot adoption through two additional tests. First, I provided evidence that firms involved in domestic mergers with non-multinational Spanish firms do not begin investing in robots, possibly because they do not have access to a multinational network for exporting. Second, I documented that divested firms (those that were originally domestic, acquired by a multinational, and then sold to a non-multinational Spanish owner) have a lower probability of adopting robots compared to those that remain under multinational ownership. This may be because these divested firms do not gain stable foreign market access through their multinational parent and therefore have little incentive to increase production. The results are available upon request.

[15] It is straightforward to extend the model in Section 4 to feature investment in multiple technologies.

[16] I use a TWFE estimator to include multiple binary indicators in the regression, which the Sun and Abraham (2021) estimator does not allow for.

market outcomes than other more traditional capital-intensive technology is consistent with Acemoglu and Restrepo (2020).

5.5 Dealing with Selection

Selection into Multinational Acquisitions. Multinational takeovers are not random, and the pre-trends in Figures 3 and 4 may raise concerns that acquired firms would have reduced their labor share and adopted robots even in the absence of the acquisition. The ideal way to deal with this issue is to randomly assign multinational ownership to otherwise identical firms and see if treated firms reduce their labor share via robot adoption. Unfortunately, this approach is unfeasible. To make progress, I build upon previous literature and use a matching algorithm (Arnold and Javorcik, 2009; Guadalupe et al., 2012; Koch and Smolka, 2019).

I proceed in two steps. First, using a nearest neighborhood algorithm, I match each acquired firm to the most similar five domestic producers in terms of observable characteristics in trends (to account for differences in growth) and levels (to account for differences in size). If the algorithm cannot find five matches for some firms, it selects the most similar $N < 5$ ones.[17] The goal is to account for all the relevant observable predictors of the acquisition. I match firms based on their sales growth rate, level of sales, value added, employment, labor costs, investment, fixed assets, R&D expenditure, export values, and the number of export destinations. All variables refer to the year before the acquisition and, except the sales growth rate, are in logs.

The matched sample includes all the original multinational affiliates and 370 domestic producers. Table B.12 shows the average of each characteristic for the two groups before and after treatment, and the p-value associated with the null hypothesis that they are equal. Before matching, there are economically sizable average differences between the two groups. After matching, the two groups are balanced, and the p-value of the equality of means test is never lower than 97%.

In the second step, I estimate equation (8) on the matched sample. Identification rests on the assumption that, conditional on the included fixed effects and post-matching, multinational acquisitions are as good as random. All the results presented so far are robust to using this restricted sample of nearest neighbors as a counterfactual for acquired firms. See Figures C.11 and C.12 (where the pre-trends are flatter than in Figures 3 and 4) and Tables B.14, B.15, B.16, and B.17. These results support the idea that post-

[17] 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.

acquisition changes do not merely reflect pre-existing differences between firms, and that multinational takeovers are a conduit of organizational change on top of them.

Selection into Robot Adoption. Equation (7) in the model highlights that robot adoption is also not random. Whereas the lack of pre-trends in Figure 5 holds back the hypothesis that firms would have reduced the labor share even in the absence of robot adoption, unobserved firm-level transitory shocks that correlate with the adoption and its outcomes may bias the estimates (Blundell and Costa Dias, 2009).

Absent experimental variation in the assignment of robots across firms, I resort again to nearest neighborhood matching. The implementation of the algorithm follows the same steps as for the case of multinational acquisitions.[18] Table B.12 shows the covariates balancing between the group of firms adopting robots and those who do not before and after matching. Figure C.13 confirms that the labor share reduction in Figure 5 is robust to using this restricted sample of nearest neighbors as a counterfactual for robot adopters.

6 Industry-Level Dynamics

This section investigates the industry-level implications of within-firm labor share changes due to multinational investment and robot adoption.

6.1 Implementation

I estimate the two following pooled versions of equation (8):

$$R_{ft} = \beta_1 MNE_{ft} + \alpha_f + \alpha_t + u_{ft}, \tag{9}$$

$$LS_{ft} = \beta_2 R_{ft} + \delta_f + \delta_t + v_{ft}. \tag{10}$$

R_{ft} is an indicator equal to 1 since the first year firm f adopts a robot. LS_{ft} is the labor share of firm f in year t. 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. u_{ft} and v_{ft} are error terms. I do not impose any assumptions on their covariance.

Equations (9) and (10) are a system of two equations describing the relationship between multinational ownership, robot adoption, and the labor share. Simulating these equations forward while shutting down the contribution of multinational ownership or

[18] The results are also robust to performing the matching separately within the sub-set of acquired versus always domestic firms.

robot adoption delivers counterfactual firm-level labor share paths, which I then aggregate at the industry level using firms' observed employment shares as weights.

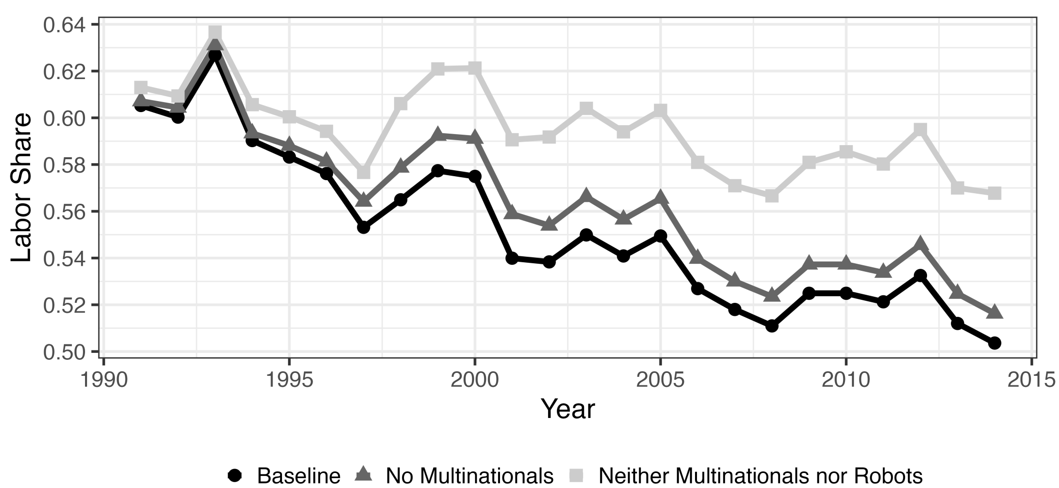
I consider two counterfactual scenarios. In the first, I shut down the role of multinational ownership. I substitute equation (9) inside equation (10) and set $MNE_{ft} = 0$. I also discount affiliates' $\widehat{\alpha}_f$ and $\widehat{\delta}_f$ to account for their correlation with the multinational status. In the second scenario, I simultaneously turn off the contribution multinational ownership and robot adoption. I set $MNE_{ft} = 0$ and discount affiliates' and robot adopters' $\widehat{\alpha}_f$ and $\widehat{\delta}_f$ to account for their correlation with the multinational and robot adopter status, respectively.

The first scenario enables the quantification of the labor share changes resulting from robot adoption induced by multinational acquisitions. The second scenario is informative about the overall role of multinationals and robots in driving changes in the labor share. In each scenario, I simulate labor share changes using 1000 bootstrap replications from the joint empirical distribution of $(\widehat{u}_{ft}, \widehat{v}_{ft})$ and report the average counterfactual outcome across replications. See Appendix D (Section D.3) for more details about implementation.

6.2 Results

Figure 6 shows the results. The black line is the actual labor share path. The observed

Figure 6. 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 multinationals. The light gray line shows the counterfactual path absent multinationals and robots.

labor share declines by about 10 percentage points (16%) over the sample period. The dark gray line is the counterfactual labor share absent multinationals. In this scenario, the reduction would have been about 9 percentage points (15%). The light gray line is the counterfactual labor share absent multinationals and robots. In this case, the reduction would have been about 5 percentage points (7%), and the counterfactual labor share in 2014 would equal its actual level of two decades earlier. Comparing the counterfactual scenarios reveals that robot adoption induced by multinational acquisitions explains about 20% of this increase.

Although Figure 6 is only informative about partial equilibrium effects and is silent about welfare, it offers a new insight on the manufacturing labor share decline. Grossman and Oberfield (2022) include globalization and automation among the leading explanations. Figure 6 reinforces and extends their argument. Rather than alternative forces, globalization (in the form of MNEs) and technological change (in the form of robots) may interact and jointly shape the observed negative trend.

7 Conclusions

This paper provides evidence that firms acquired by multinationals experience a reduction in their labor share, and emphasizes that the systematic adoption of robots taking place after the acquisition is a key driver of this reduction. The analysis is based on data from the Spanish manufacturing sector and guided by a model of robot adoption with heterogeneous firms. Additional evidence from a new cross-country industry-level dataset suggests that this pattern extends beyond the Spanish context.

Counterfactual results indicate that, without multinationals and robots, the labor share in the Spanish manufacturing sector would return to its level from two decades ago, shedding new light on the interaction between globalization (in the form of MNEs) and technological change (in the form of robots) in shaping the labor share reduction observed across many countries in the world.

Recent literature provides evidence that the impact of robots 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 that I document in this article may be a lower bound to the economy-wide ones.

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Appendix

A Data

A.1 Firm-Level Data

I deal with missing data in the ESEE survey using a forward imputation criterion. If a binary variable (e.g., multinational ownership, technology adoption, type of activity) is missing, I impute its value with the first non-missing previous value. If a continuous variable is missing (e.g., sales, employment, cost and prices, investment, physical inputs), 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.

Notwithstanding its richness, the ESEE data also come with some limitations. First, firms do not disclose the identity of their multinational owners. This limitation prevents distinguishing between vertical and horizontal FDI and testing if parents headquartered in countries where robots are highly diffused are more likely to spur robot adoption than parents located elsewhere. Second, the survey does not report if a firm is owned by a multinational with headquarters in Spain, which precludes including firms acquired by a Spanish multinational in the sample. However, the theory in Section 4 suggests that the empirical results in Section 5 would hold for these acquisitions as well. Finally, the survey does not report information about expenditure on robots (i.e., the intensive margin).

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. The procedure consists of two steps. In the first step, I take as initial value the first available data about the number of deployed robots at the country-industry level. In the second one, I calculate subsequent values using the information about new installations and assuming a yearly depreciation rate of 10%. Second, about 20% of the stock cannot be allocated to any industry in some countries. 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 the following sectors: "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, Tukey and the USA.

I express nominal variables in previous-year prices using the one-digit domestic output deflator provided by WIOD SEA.

B Tables

Table B.1. Acquisitions by Year

Year	Number of New Acquisitions
1991	14
1992	11
1993	5
1994	1
1995	8
1996	4
1997	5
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	5
2014	5

Note: The Table reports the number of multinational acquisitions by year.

Table B.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	1.41	4.07	21.35
Total RD Expenses	0.07	1.45	1.09	2.80
Internal RD	0.05	0.92	0.79	2.03
Panel D: Other Characteristics				
Sales	9.09	41.70	106.90	333.32
Value Added	2.57	9.64	27.51	75.91
Labor Costs	22.44	10.21	30.90	12.90
Intermediate Inputs	6.68	34.32	81.66	268.97
Labor Share	0.63	0.27	0.57	0.25
Employees	64.31	199.16	557.34	1201.99
Fixed Assets	4.67	22.08	89.09	364.09
Exporter	0.45	0.50	0.82	0.38
Export Value	2.23	16.02	32.01	106.53
No. of Export Markets	0.43	0.81	1.16	1.18

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, which is in percentage terms, the number of employees and export markets, which are a count, and the exporter variable, which is a binary indicator. Variables are defined in Table B.3.

Table B.3. Variables' Description

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

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".

Table B.4. 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 panel that I describe in Section 2.2.

Table B.5. Multinational Production, Labor Share, and Robot Adoption

Dependent Variables:	Labor Share$_{cit}$			Log(Robots per 1000 Employees)$_{cit}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Multinational Production)$_{cit}$	-0.05***	-0.02***	-0.008***	1.7***	0.55***	0.24***
	(0.002)	(0.008)	(0.003)	(0.04)	(0.08)	(0.09)
Controls	No	No	Yes	No	No	Yes
Country-Industry FE	No	Yes	Yes	No	Yes	Yes
Year FE	No	Yes	Yes	No	Yes	Yes
Observations	6,514	6,514	6,514	6,514	6,514	6,514
Estimator	OLS	OLS	OLS	OLS	OLS	OLS

Note: The unit of observation is industry i of country c at time t (2005 - 2014). Labor Share$_{cit}$ is the ratio between expenditure on labor and variable production cost (i.e., expenditure on capital and labor). Log(Robots per 1000 Employees)$_{cit}$ is the log of the number of industrial robots per thousand employees. Log(Multinational Production)$_{cit}$ is the log of the gross output produced by multinational-owned firms. I standardize the log of multinational production to have zero mean and unit variance in the sample. "Controls" are the log of the number of employees, labor costs, capital stock, and interest rate at the country-industry-year level. Heteroscedasticity-robust standard errors in parenthesis. Significance levels: *** 0.01, ** 0.05, * 0.1.

Table B.6. Why Do Multinationals Adopt Robots? /1

Dependent Variables:	Log(Value Added)$_{ft}$	Exp. via Foreign Parent$_{ft}$	Log(Ext. R&D/Employees)$_{ft}$	Imp. of Foreign Tech.$_{ft}$
	(1)	(2)	(3)	(4)
MNE$_{ft}$	0.23***	0.36***	0.31	0.01
	(0.07)	(0.04)	(0.32)	(0.04)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	13,833	13,833	13,833	13,833
Estimator	SA	SA	SA	SA

Note: The unit of observation is a firm-year pair. I only use observations for which all variables are non-missing. I obtain similar results if I use all available observations for each variable separately. Log(Value Added)$_{ft}$ is the log of firm f value added in production at time t. Exp. via Foreign Parent$_{ft}$ is binary variable equal to 1 if firm f exports via its multinational parental network at time t and zero if it uses an alternative channel (e.g., own means, specialized intermediaries, collective actions, or other means). Log(Ext. R&D/Employees)$_{ft}$ is the log of one plus the expenditure on external R&D per employee. Hence, it accounts both for the intensive and extensive margins of external R&D. Imp. of Foreign Tech.$_{ft}$ is binary variable equal to 1 if firm f imports licenses and technical aid from abroad at time t and 0 otherwise. MNE$_{ft}$ is a binary variable 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. The acronym "SA" stands for Sun and Abraham (2021).

Table B.7. Multinationals and Export Sales

Dependent Variable:	Log(Exports)$_{ft}$	
	(1)	(2)
MNE$_{ft}$	0.11	0.12
	(0.19)	(0.19)
Small$_{ft}$		-0.57***
		(0.09)
Small$_{ft}$ $\times$ MNE$_{ft}$ $= 1$		1.2***
		(0.20)
Firm FE	Yes	Yes
Year FE	Yes	Yes
Observations	11,118	11,118
Estimator	OLS	OLS

Note: The unit of observation is a firm-year pair. Log(Export)$_{ft}$ is the log of the export value. MNE$_{ft}$ is a binary variable equal to 1 if firm f is multinational-owned in year t and 0 otherwise. Small$_{ft}$ is a binary indicator equal to 1 if firm f reports sales below the sample median in year t and 0 otherwise. I use the OLS estimator to allow for interaction between MNE$_{ft}$ and Small$_{ft}$. Cluster standard errors at the firm level in parenthesis. Significance levels: *** 0.01, ** 0.05, * 0.1.

Table B.8. Why Do Multinationals Adopt Robots? /2

Dependent Variable:	Robot Adoption$_{ft}$			
	(1)	(2)	(3)	(4)
Log(Value Added)$_{ft}$	0.003	0.002	0.002	0.001
	(0.008)	(0.008)	(0.008)	(0.008)
Exp. via Foreign Parent$_{ft}$		0.20***	0.20***	0.20***
		(0.06)	(0.06)	(0.06)
Log(Ext. R&D/Employees)$_{ft}$			0.002	0.002
			(0.002)	(0.002)
Imp. of Foreign Tech.$_{ft}$				0.01
				(0.03)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	13,834	13,834	13,834	13,834
Estimator	OLS	OLS	OLS	OLS

Note: The unit of observation is a firm-year pair. I only use observations for which all variables are non-missing. I obtain similar results if I use all available observations for each variable separately. Robot Adoption$_{ft}$ is a binary variable equal to 1 since the first year firm f adopts a robot. Log(Value Added)$_{ft}$ is the log of firm f value added in production at time t. Exp. via Foreign Parent$_{ft}$ is binary variable equal to 1 if firm f exports via its multinational parental network at time t and zero if it uses an alternative channel (e.g., own means, specialized intermediaries, collective actions, or other means). Log(Ext. R&D/Employees)$_{ft}$ is the log of one plus the expenditure on external R&D per employee. Hence, it accounts both for the intensive and extensive margins of external R&D. Imp. of Foreign Tech.$_{ft}$ is binary variable equal to 1 if firm f imports licenses and technical aid from abroad at time t and 0 otherwise. Cluster standard errors at the firm level in parenthesis. Significance levels: *** 0.01, ** 0.05, * 0.1.

Table B.9. Type of Manufacturing

Dependent Variables:	Batch Manuf.$_{ft}$	Mass Manuf.$_{ft}$	Mixed Manuf.$_{ft}$	Continuous Manuf.$_{ft}$
	(1)	(2)	(3)	(4)
MNE$_{ft}$	-0.12*	0.02	0.02	0.08***
	(0.07)	(0.07)	(0.02)	(0.02)
Firm FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Observations	23,573	23,573	23,573	23,573
Estimator	SA	SA	SA	SA

Note: The unit of observation is a firm-year pair. Batch Manuf.$_{ft}$ is a binary variable equal to 1 if firm f performs batch manufacturing in year t and 0 otherwise. Mass Manuf.$_{ft}$ is a binary variable equal to 1 if firm f performs mass manufacturing in year t and 0 otherwise. Mixed Manuf.$_{ft}$ is a binary variable equal to 1 if firm f performs mixed manufacturing in year t and 0 otherwise. Continuous Manuf.$_{ft}$ is a binary variable 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 variable 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. The acronym "SA" stands for Sun and Abraham (2021).

Table B.10. Other Types of Investment

Dependent Variables:	Other Automation$_{ft}$	CAD Manufacturing$_{ft}$
	(1)	(2)
MNE$_{ft}$	-0.04**	0.09**
	(0.02)	(0.04)
Firm FE	Yes	Yes
Industry-Year FE	Yes	Yes
Observations	24,106	24,106
Estimator	SA	SA

Note: The unit of observation is a firm-year pair. Other Automation$_{ft}$ is a binary variable equal to 1 since the first year firm f uses flexible systems or numerically controlled machines. CAD Manufacturing$_{ft}$ is a binary variable equal to 1 since the first year firm f uses CAD manufacturing. MNE$_{ft}$ is a binary variable equal to 1 if firm f is multinational-owned in year t and 0 otherwise. These activities are not mutually exclusive. Cluster standard errors at the firm level in parenthesis. Significance levels: *** 0.01, ** 0.05, * 0.1. The acronym "SA" stands for Sun and Abraham (2021).

Table B.11. Labor Share and Different Types of Investment

Dependent Variable:	Labor Share$_{ft}$			
	(1)	(2)	(3)	(4)
Robot Adoption$_{ft}$	-0.04***	-0.04***	-0.04***	-0.04***
	(0.009)	(0.009)	(0.009)	(0.009)
Other Automation$_{ft}$		0.002	-0.001	-0.002
		(0.007)	(0.007)	(0.007)
CAD Manufacturing$_{ft}$			0.02***	0.02***
			(0.008)	(0.008)
Batch Manuf.$_{ft}$				0.06
				(0.04)
Mass Manuf.$_{ft}$				0.05
				(0.04)
Mixed Manuf.$_{ft}$				0.04
				(0.04)
Continuous Manuf.$_{ft}$				0.04
				(0.04)
Firm FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Observations	24,107	24,107	24,107	23,574
Estimator	OLS	OLS	OLS	OLS

Note: The unit of observation is a firm-year pair. Labor Share$_{ft}$ is the labor share of firm f at time t. Robot Adoption$_{ft}$ is a binary variable equal to 1 since the first year firm f uses robots. Other Automation$_{ft}$ is a binary variable equal to 1 since the first year firm f uses flexible systems or numerically controlled machines. CAD Manufacturing$_{ft}$ is a binary variable equal to 1 since the first year firm f uses CAD manufacturing. These activities are not mutually exclusive. Batch Manuf.$_{ft}$ is a binary variable equal to 1 if firm f performs batch manufacturing in year t and 0 otherwise. Mass Manuf.$_{ft}$ is a binary variable equal to 1 if firm f performs mass manufacturing in year t and 0 otherwise. Mixed Manuf.$_{ft}$ is a binary variable equal to 1 if firm f performs mixed manufacturing in year t and 0 otherwise. Continuous Manuf.$_{ft}$ is a binary variable equal to 1 if firm f performs continuous manufacturing in year t and 0 otherwise. These activities are mutually exclusive. Significance levels: *** 0.01, ** 0.05, * 0.1.

Table B.12. 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	0.04	0.88	0.97
Lag Log Sales	16.76	14.58	16.79	0.16	0.98
Lag Log Value Added	15.61	13.55	15.64	0.19	0.99
Lag Log Employment	5.20	3.42	5.20	0.17	1.00
Lag Log Labor Costs	3.25	3.04	3.24	0.61	0.97
Lag Log Investment	11.84	7.70	11.95	0.34	0.98
Lag Log Fixed Assets	15.79	13.37	15.81	0.21	0.99
Lag Log RD Expenditure	6.91	1.95	6.87	0.45	0.99
Lag Log Exports	11.38	5.74	11.11	0.40	0.97
Lag Log Number of Export Markets	0.52	0.25	0.51	0.63	0.99

Note: The Table shows the goodness of fit of the matching algorithm. 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 B.13. 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	0.96
Lag Log Sales	15.42	14.30	15.40	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	3.00	3.15	0.70	0.99
Lag Log Investment	9.57	7.13	9.35	0.63	0.96
Lag Log Fixed Assets	14.50	12.95	14.47	0.40	0.99
Lag Log RD Expenditure	3.95	1.49	3.89	0.67	0.99
Lag Log Exports	8.25	4.94	8.16	0.64	0.99
Lag Log Number of Export Markets	0.35	0.22	0.35	0.77	0.99

Note: The Table shows the goodness of fit of the matching algorithm. 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 B.14. Why Do Multinationals Adopt Robots? /1 (Matching)

Dependent Variables:	Log(Value Added)$_{ft}$	Exp. via Foreign Parent$_{ft}$	Log(Ext. R&D/Employees)$_{ft}$	Imp. of Foreign Tech.$_{ft}$
	(1)	(2)	(3)	(4)
MNE$_{ft}$	0.17**	0.36***	-0.01	0.03
	(0.08)	(0.04)	(0.35)	(0.04)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	3,164	3,164	3,164	3,164
Estimator	SA	SA	SA	SA

Note: The unit of observation is a firm-year pair. I only use observations pertaining to the matched sample described in Section 5.5. Exp. via Foreign Parent$_{ft}$ is binary variable equal to 1 if firm f exports via its multinational parental network at time t and zero if it uses an alternative channel (e.g., own means, specialized intermediaries, collective actions, or other means). Log(Ext. R&D/Employees)$_{ft}$ is the log of one plus the expenditure on external R&D per employee. Hence, it accounts both for the intensive and extensive margins of external R&D. Imp. of Foreign Tech.$_{ft}$ is binary variable equal to 1 if firm f imports licenses and technical aid from abroad at time t and 0 otherwise. MNE$_{ft}$ is a binary variable 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. The acronym "SA" stands for Sun and Abraham (2021).

Table B.15. Why Do Multinationals Adopt Robots? /2 (Matching)

Dependent Variable:	Robot Adoption$_{ft}$			
	(1)	(2)	(3)	(4)
Log(Value Added)$_{ft}$	0.02	0.02	0.01	0.01
	(0.02)	(0.02)	(0.02)	(0.02)
Exp. via Foreign Parent$_{ft}$		0.17***	0.17***	0.17***
		(0.06)	(0.06)	(0.06)
Log(Ext. R&D/Employees)$_{ft}$			0.002	0.002
			(0.003)	(0.003)
Imp. of Foreign Tech.$_{ft}$				0.01
				(0.04)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	3,165	3,165	3,165	3,165
Estimator	OLS	OLS	OLS	OLS

Note: The unit of observation is a firm-year pair. I only use observations pertaining to the matched sample described in Section 5.5. Robot Adoption$_{ft}$ is a binary variable equal to 1 since the first year firm f adopts a robot. Exp. via Foreign Parent$_{ft}$ is binary variable equal to 1 if firm f exports via its multinational parental network at time t and zero if it uses an alternative channel (e.g., own means, specialized intermediaries, collective actions, or other means). Log(Ext. R&D/Employees)$_{ft}$ is the log of one plus the expenditure on external R&D per employee. Hence, it accounts both for the intensive and extensive margins of external R&D. Imp. of Foreign Tech.$_{ft}$ is binary variable equal to 1 if firm f imports licenses and technical aid from abroad at time t and 0 otherwise. Cluster standard errors at the firm level in parenthesis. Significance levels: *** 0.01, ** 0.05, * 0.1.

Table B.16. Type of Manufacturing (Matching)

Dependent Variables:	Batch Manuf.$_{ft}$	Mass Manuf.$_{ft}$	Mixed Manuf.$_{ft}$	Continuous Manuf.$_{ft}$
	(1)	(2)	(3)	(4)
MNE$_{ft}$	-0.09	-0.006	0.01	0.08***
	(0.07)	(0.07)	(0.02)	(0.03)
Firm FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Observations	3,974	3,974	3,974	3,974
Estimator	SA	SA	SA	SA

Note: The unit of observation is a firm-year pair. I only use observations pertaining to the matched sample described in Section 5.5. Batch Manuf.$_{ft}$ is a binary variable equal to 1 if firm f performs batch manufacturing in year t and 0 otherwise. Mass Manuf.$_{ft}$ is a binary variable equal to 1 if firm f performs mass manufacturing in year t and 0 otherwise. Mixed Manuf.$_{ft}$ is a binary variable equal to 1 if firm f performs mixed manufacturing in year t and 0 otherwise. Continuous Manuf.$_{ft}$ is a binary variable 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 variable 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. The acronym "SA" stands for Sun and Abraham (2021).

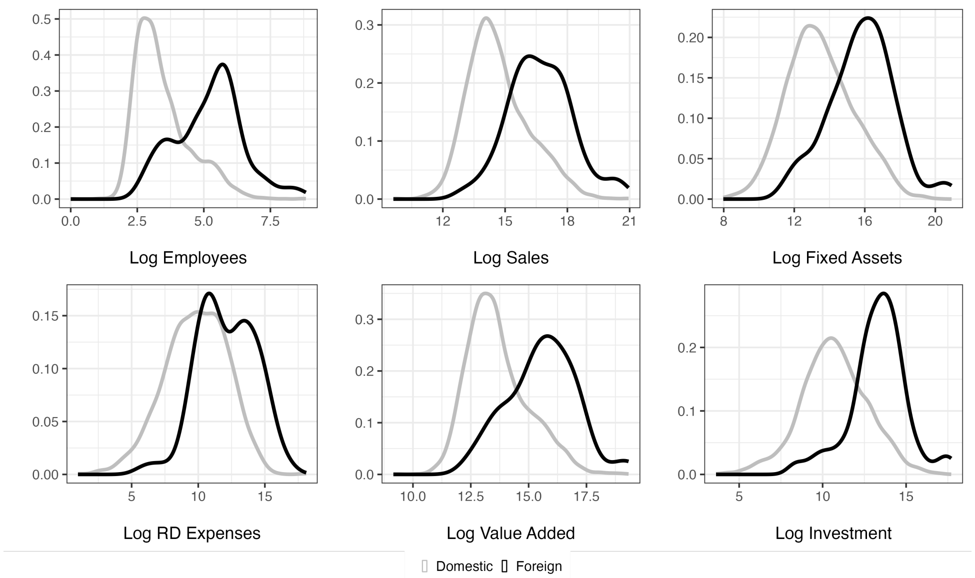
Table B.17. Other Types of Investment (Matching)

Dependent Variables:	Other Automation$_{ft}$	CAD Manufacturing$_{ft}$
	(1)	(2)
MNE$_{ft}$	-0.07***	0.08**
	(0.03)	(0.04)
Firm FE	Yes	Yes
Industry-Year FE	Yes	Yes
Observations	3,988	3,988
Estimator	SA	SA

Note: The unit of observation is a firm-year pair. I only use observations pertaining to the matched sample described in Section 5.5. Other Automation$_{ft}$ is a binary variable equal to 1 if firm f uses flexible systems or numerically controlled machines in year t and 0 otherwise. CAD Manufacturing$_{ft}$ is a binary variable equal to 1 if firm f uses CAD manufacturing in year t and 0 otherwise. MNE$_{ft}$ is a binary variable equal to 1 if firm f is multinational-owned in year t and 0 otherwise. These activities are not mutually exclusive. Cluster standard errors at the firm level in parenthesis. Significance levels: *** 0.01, ** 0.05, * 0.1. The acronym "SA" stands for Sun and Abraham (2021).

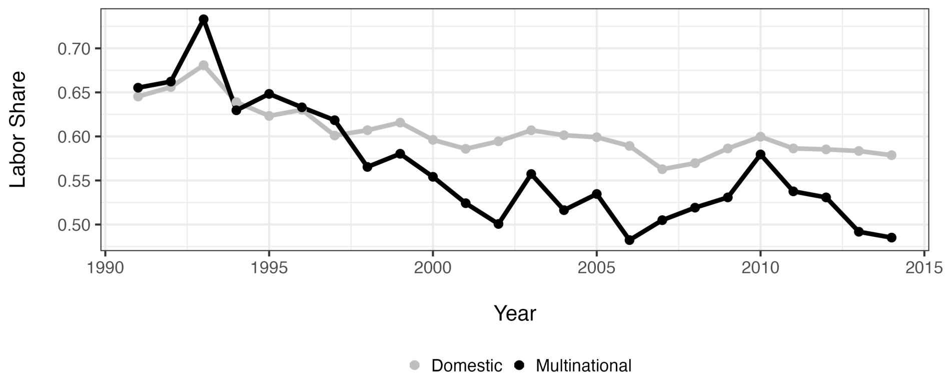
C Figures

Figure C.1. Density Plots by Ownership



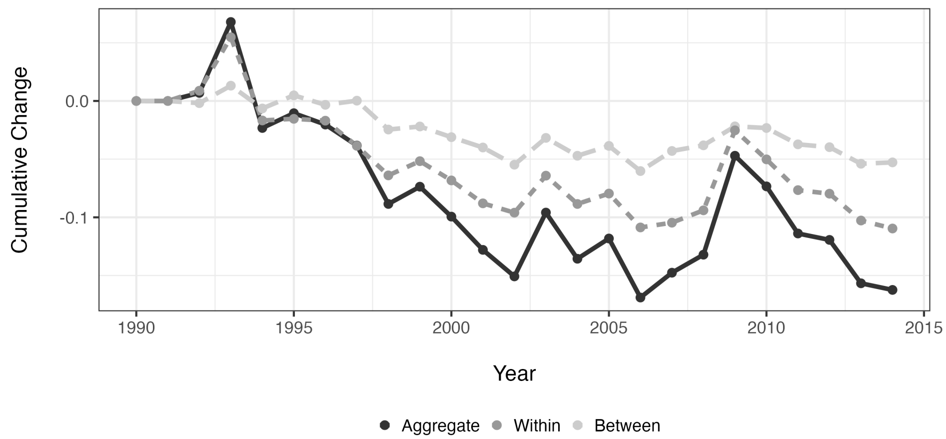
Note: The Figure shows the empirical probability density function (pdf) of the log of employees, sales, fixed assets, R&D expenses, value added, and investment by ownership type. I estimate the empirical pdf for domestic-owned firms based on their lifetime characteristics. I estimate it only for the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

Figure C.2. Labor Share by Ownership - Conditional on Firm Size



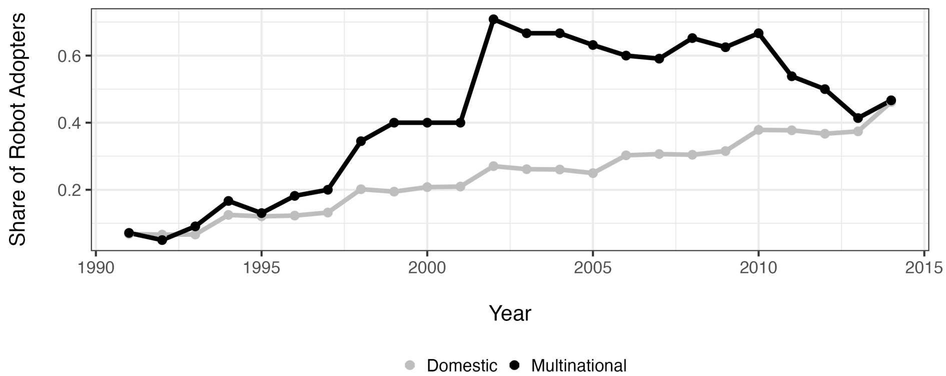
Note: The Figure shows the labor share trends by ownership. Differently from Figure 1, I only include domestic firms above the sample median of the employment distribution.

Figure C.3. Decomposition of the Labor Share



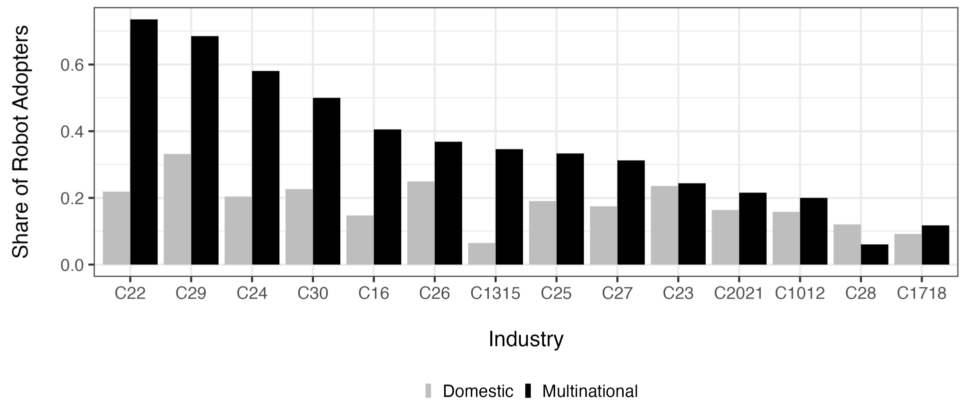
Note: The Figure shows the cumulative change in the Spanish manufacturing labor share and its two components in equation (1) over time. The black solid line is the total cumulative change. The dark gray dotted line shows the within-group change, whereas the dashed light gray line is the between-group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

Figure C.4. Share of Robot Adopters by Ownership - Conditional on Firm Size



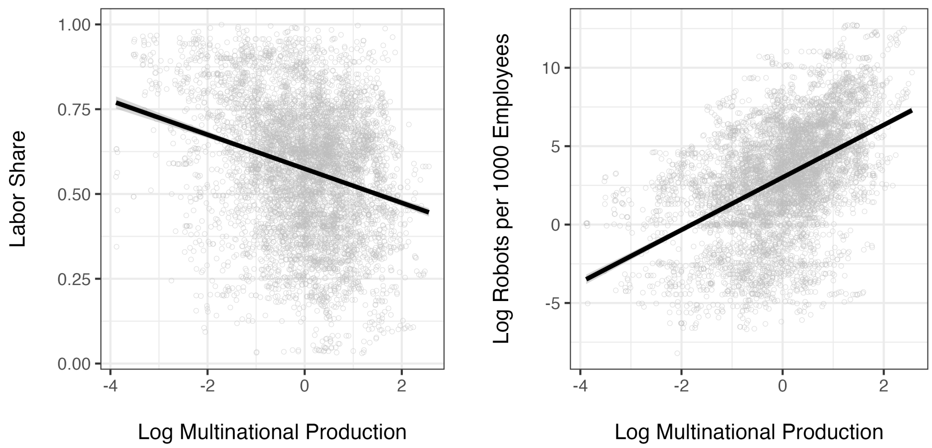
Note: The Figure shows the share of robot adopters by ownership. Differently from Figure 2, I only include domestic firms above the sample median of the employment distribution.

Figure C.5. Robot Adoption by Ownership and Industry



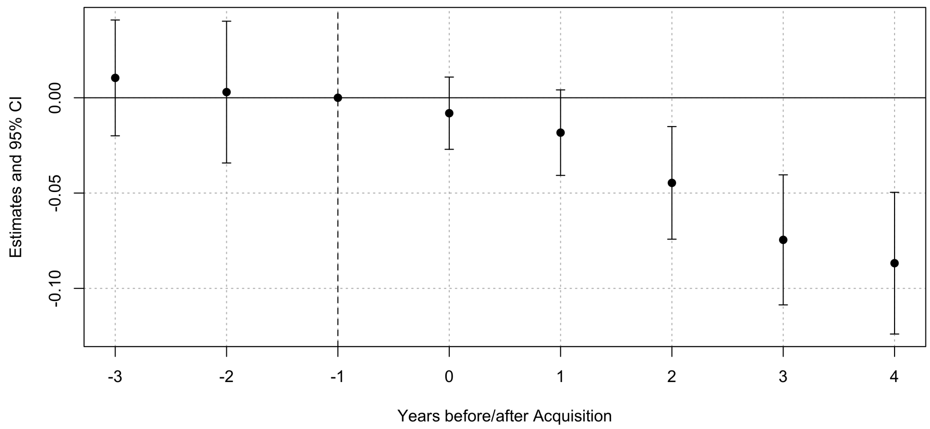
Note: The Figure shows the share of robot adopters by ownership type across industries. The shares are computed as an average across all sample years.

Figure C.6. Multinational Production, Labor Share, and Robots



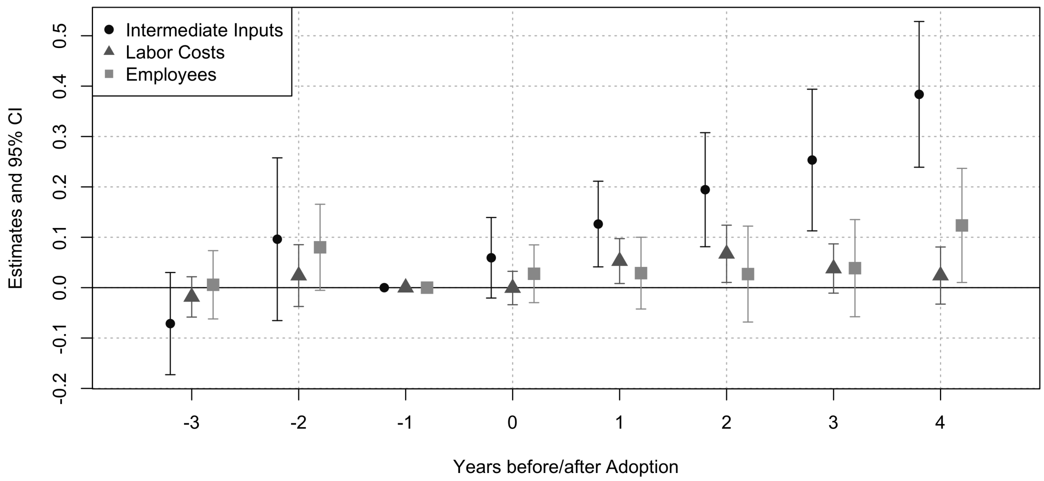
Note: The left panel of the Figure shows the correlation between the labor share and the log of multinational production in industry i of country c at time t. The right panel shows the correlation between the log of the number of industrial robots per thousand employees and the log of multinational production in industry i of country c at time t. I standardize the log of multinational production to have zero mean and unit variance in the sample.

Figure C.7. Multinational Ownership and the Labor Share (Industry Trends)



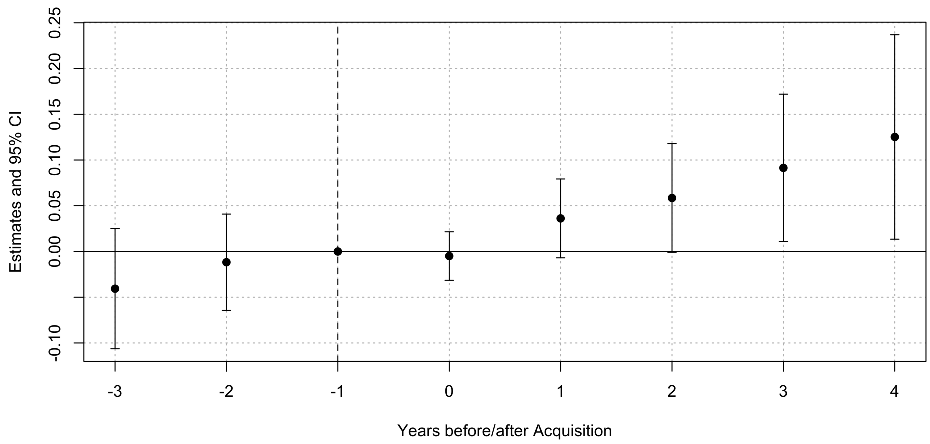
Note: The Figure reproduces Figure 3 replacing year fixed effects with industry-by-year fixed effects. The unit of observation is a firm-year pair. There are 24,106 observations. I cluster standard errors at the firm level. I report the estimates for $[\underline{k}, \bar{k}] = [-3, 4]$.

Figure C.8. Labor Share Components



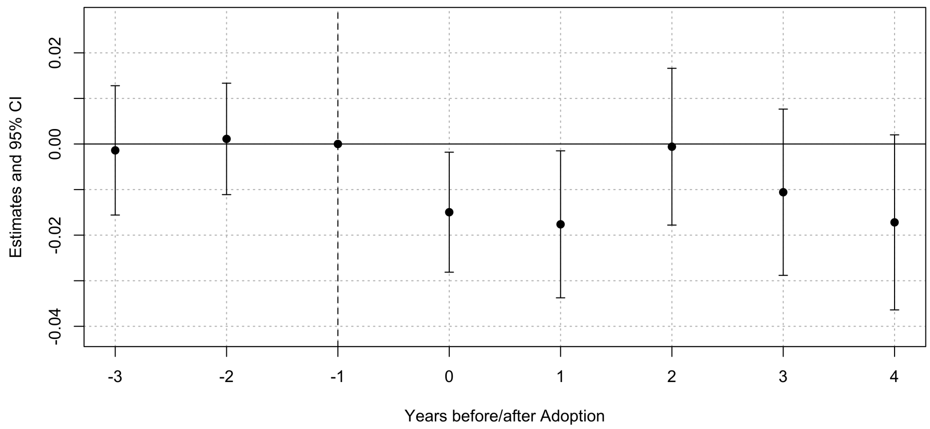
Note: The Figure plots the estimates I obtain from equation (8) using (the log of) expenditure on intermediate inputs (i.e., material inputs and external services), labor costs, and the number of employees as the dependent variable and the leads and lags of a binary indicator equal to 1 if firm f is owned by a multinational at time t as the independent variable.. The unit of observation is a firm-year pair. There are 24,106 observations. I cluster standard errors at the firm level. I report the estimates for $[\underline{k}, \bar{k}] = [-3, 4]$.

Figure C.9. Multinational Ownership and Robot Adoption (Industry Trends)



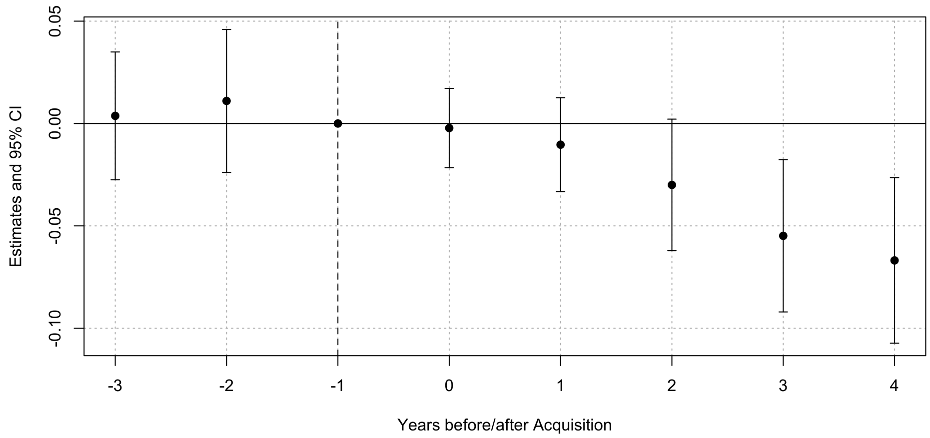
Note: The Figure reproduces Figure 4 replacing year fixed effects with industry-by-year fixed effects. The unit of observation is a firm-year pair. There are 24,106 observations. I cluster standard errors at the firm level. I report the estimates for $[\underline{k}, \bar{k}] = [-3, 4]$.

Figure C.10. Robot Adoption and the Labor Share (Industry Trends)



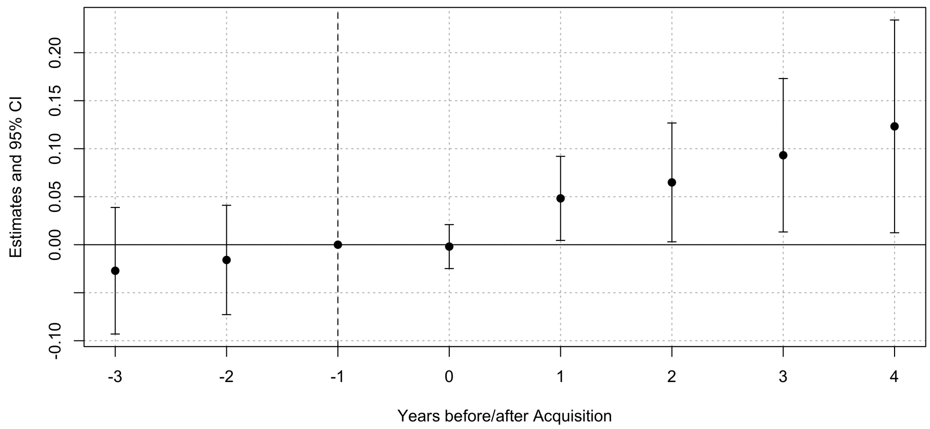
Note: The Figure reproduces Figure 5 replacing year fixed effects with industry-by-year fixed effects. The unit of observation is a firm-year pair. There are 24,106 observations. I cluster standard errors at the firm level. I report the estimates for $[\underline{k}, \bar{k}] = [-3, 4]$.

Figure C.11. Multinationals and the Labor Share (Matching)



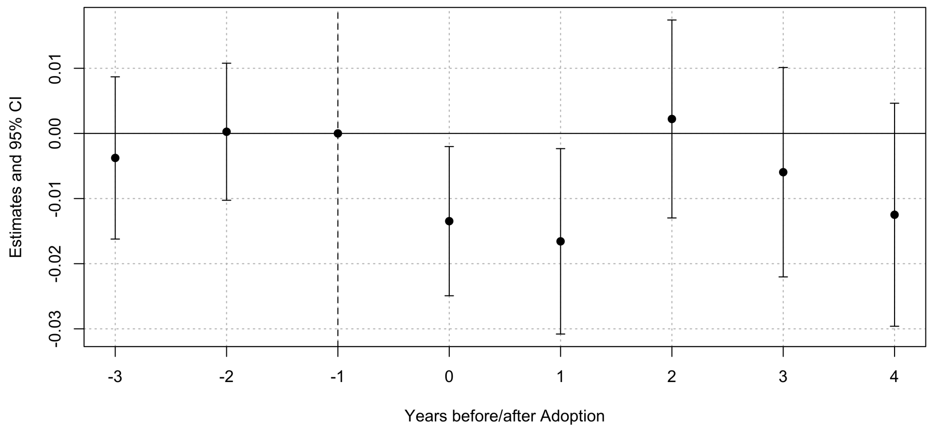
Note: The Figure plots the estimates I obtain from equation (8) using the labor share as the dependent variable and the leads and lags of a binary indicator equal to 1 if firm f is owned by a multinational at time t as the independent variable. The unit of observation is a firm-year pair. I only use observations pertaining to the matched sample described in Section 5.5. There are 3,988 observations. I cluster standard errors at the firm level. I report the estimates for $[\underline{k}, \bar{k}] = [-3, 4]$.

Figure C.12. Multinationals and Robot Adoption (Matching)



Note: The Figure plots the estimates I obtain from equation (8) using a binary indicator equal to 1 since the first year firm f adopts a robot as the dependent variable and the leads and lags of a binary indicator equal to 1 if firm f is owned by a multinational at time t as the independent variable.The unit of observation is a firm-year pair. I only use observations pertaining to the matched sample described in Section 5.5. There are 3,988 observations. I cluster standard errors at the firm level. I report the estimates for $[\underline{k}, \bar{k}] = [-3, 4]$.

Figure C.13. Robot Adoption and the Labor Share (Matching)



Note: The Figure plots the estimates I obtain from equation (8) using the labor share as the dependent variable and the leads and lags of a binary indicator equal to 1 since the first year firm f adopts a robot as the independent variable.The unit of observation is a firm-year pair. I only use observations pertaining to the matched sample described in Section 5.5. There are 3,988 observations. I cluster standard errors at the firm level. I report the estimates for $[\underline{k}, \bar{k}] = [-3, 4]$.

D Theoretical Appendix

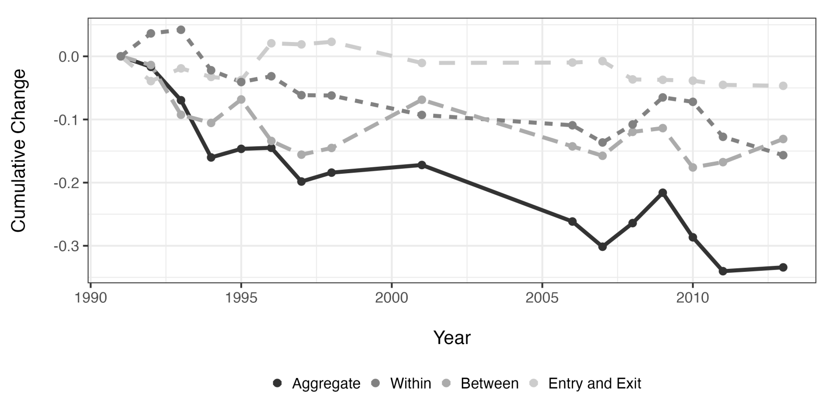
D.1 Decomposing the Labor Share of Multinational Affiliates

Following Autor et al. (2020), I express the changes in the manufacturing labor share between year $t-1$ and t as follows:[19]

$$\Delta LS_t = \Delta\overline{ls}_{St} + \Delta cov(s_{St}, ls_{St}) + s_{Et}(\overline{ls}_{Et} - \overline{ls}_{St}) + s_{Xt-1}(\overline{ls}_{St-1} - \overline{ls}_{Xt-1}) \qquad \text{(D.1)}$$

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 at time 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 D.1, I apply equation (D.1) 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.

Figure D.1. Decomposition of the Labor Share and its Components



Note: The Figure shows the cumulative change in the manufacturing labor share of multinational affiliates and its components in equation (D.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 gray line is the between-group change. The long-dashed light gray line is the entry-exit component.

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

D.2 Proofs of Propositions

Proof of Proposition 1. The labor share of firm f at time t is:

$$LS_{ft} = \frac{w_t L_{ft}}{w_t L_{ft} + r_t M_{ft}} \tag{D.1}$$

$$= \frac{\beta_{ft}(R_{ft})^{\frac{1}{\sigma}} L_{ft}^{\frac{\sigma-1}{\sigma}}}{\beta_{ft}(R_{ft})^{\frac{1}{\sigma}} L_{ft}^{\frac{\sigma-1}{\sigma}} + \alpha_{ft}(R_{ft})^{\frac{1}{\sigma}} M_{ft}^{\frac{\sigma-1}{\sigma}}} \tag{D.2}$$

$$= \frac{1}{1 + \frac{\alpha_{ft}(R_{ft})^{\frac{1}{\sigma}} M_{ft}^{\frac{\sigma-1}{\sigma}}}{\beta_{ft}(R_{ft})^{\frac{1}{\sigma}} L_{ft}^{\frac{\sigma-1}{\sigma}}}} \tag{D.3}$$

which is strictly decreasing in R_{ft} by Assumptions 1 and 2 (see also Acemoglu and Restrepo, 2018).

Proof of Proposition 2. Firm f invests in robots at time t if and only if:

$$R_{ft} = 1 \iff \sum_{s=t}^{\infty} \beta^{s-t} \mathbb{E}_t \left[\tilde{\pi}_{ft}(1)\right] - FC_{ft} \geq \sum_{s=t}^{\infty} \beta^{s-t} \mathbb{E}_t \left[\tilde{\pi}_{ft}(0)\right] \tag{D.4}$$

$$\implies \sum_{s=t}^{\infty} \beta^{s-t} \mathbb{E}_t \left[D_t \psi_{ft} \delta z_{ft}^{\theta-1} \Delta\chi_{ft}\right] \geq FC_{ft}, \tag{D.5}$$

where:

$$\Delta\chi_{ft} = \left(\alpha_{ft}(1) r_t^{1-\sigma} + \beta_{ft}(1) w_t^{1-\sigma}\right)^{\frac{1-\theta}{1-\sigma}} - \left(\alpha_{ft}(0) r_t^{1-\sigma} + \beta_{ft}(0) w_t^{1-\sigma}\right)^{\frac{1-\theta}{1-\sigma}} > 0 \tag{D.6}$$

by Assumptions 1 and 2. Notice that the left-hand side of equation (D.5) is strictly increasing in z_{ft} and ψ_{ft} and strictly decreasing in FC_{ft}. Hence, firms with higher productivity, facing higher demand levels, or having lower adoption costs are more likely to adopt robots.

D.3 Counterfactuals' Implementation

I estimate the following equations:

$$R_{ft} = \beta_1 \times MNE_{ft} + \alpha_f + \alpha_t + u_{ft} \quad \text{and} \quad LS_{ft} = \beta_2 \times R_{ft} + \delta_f + \delta_t + v_{ft}. \tag{D.1}$$

R_{ft} is an indicator equal to 1 if firm f adopts robots in year t. LS_{ft} is the labor share of firm f in year t. 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 substitute the left-hand side equation inside the right-hand side one and consider two counterfactual scenarios:

- **Scenario 1 (no multinationals)**: The counterfactual firm-level labor share is:

$$LS_{ft}^{(1)} = \widehat{\beta}_2(\widehat{\alpha}_f^{(1)} + \widehat{\alpha}_t + \widehat{u}_{ft}) + \widehat{\delta}_f^{(1)} + \widehat{\delta}_t + \widehat{v}_{ft}. \tag{D.2}$$

  I set $MNE_{ft} = 0$ and re-define the estimated firm-level fixed effects as:

$$\widehat{\alpha}_f^{(1)} = \widehat{\alpha}_f - (\mathbb{E}[\widehat{\alpha}_f | MNE_{ft} = 1] - \mathbb{E}[\widehat{\alpha}_f | MNE_{ft} = 0]) \times MNE_{ft} \tag{D.3}$$
$$\widehat{\delta}_f^{(1)} = \widehat{\delta}_f - (\mathbb{E}[\widehat{\delta}_f | MNE_{ft} = 1] - \mathbb{E}[\widehat{\delta}_f | MNE_{ft} = 0]) \times MNE_{ft}. \tag{D.4}$$

  In words, if $MNE_{ft} = 1$, I subtract the multinational ownership premium from $\widehat{\alpha}_f$ and $\widehat{\delta}_f$.

- **Scenario 2 (neither multinationals nor robots)**: The counterfactual firm-level labor share is:

$$LS_{ft}^{(2)} = \widehat{\beta}_2(\widehat{\alpha}_f^{(2)} + \widehat{\alpha}_t + \widehat{u}_{ft}) + \widehat{\delta}_f^{(2)} + \widehat{\delta}_t + \widehat{v}_{ft}. \tag{D.5}$$

  I set $MNE_{ft} = 0$ and re-define the estimated firm-level fixed effects as:

$$\widehat{\alpha}_f^{(2)} = \widehat{\alpha}_f^{(1)} - (\mathbb{E}[\widehat{\alpha}_f | R_{ft} = 1] - \mathbb{E}[\widehat{\alpha}_f | R_{ft} = 0]) \times R_{ft} \tag{D.6}$$
$$\widehat{\delta}_f^{(2)} = \widehat{\delta}_f^{(1)} - (\mathbb{E}[\widehat{\delta}_f | R_{ft} = 1] - \mathbb{E}[\widehat{\delta}_f | R_{ft} = 0]) \times R_{ft}. \tag{D.7}$$

  In words, if $MNE_{ft} = 1$ and $R_{ft} = 1$, I subtract the multinational ownership and robot adoption premia from $\widehat{\alpha}_f$ and $\widehat{\delta}_f$.

In each scenario, I use 1000 bootstrap replications from the joint empirical distribution of $(\widehat{u}_{ft}, \widehat{v}_{ft})$ and report the average counterfactual LS_{ft} across replications.

E Two-Way Fixed Effects Estimator

This section reproduces the main figures and tables of this paper using a standard TWFE estimator. I reproduce Figures 3, 4, and 5, as well as Table B.6. The results are qualitatively consistent with those I get with the Sun and Abraham (2021) estimator.

E.1 Tables

Table E.1. Why Do Multinationals Adopt Robots? /1 (TWFE)

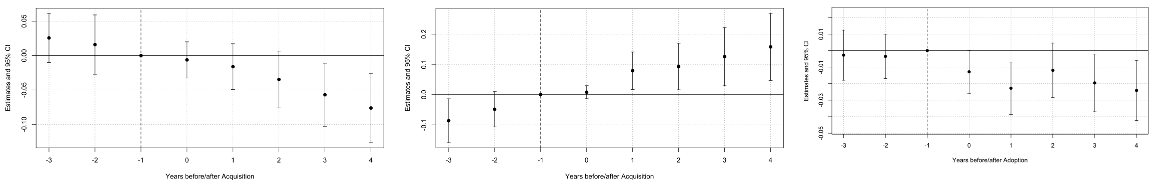
Dependent Variables:	Exp. via Foreign Parent$_{ft}$	Log(Value Added)$_{ft}$	Log(Ext. R&D/Employees)$_{ft}$	Imp. of Foreign Tech.$_{ft}$
	(1)	(2)	(3)	(4)
MNE$_{ft}$	0.30***	0.16	-0.35	0.04
	(0.05)	(0.12)	(0.36)	(0.05)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	13,834	13,834	13,834	13,834
Estimator	OLS	OLS	OLS	OLS

Note: The unit of observation is a firm-year pair. I only use observations for which all variables are non-missing. I obtain similar results if I use all available observations for each variable separately. Exp. via Foreign Parent$_{ft}$ is binary variable equal to 1 if firm f exports via its multinational parental network at time t and zero if it uses an alternative channel (e.g., own means, specialized intermediaries, collective actions, or other means). Log(Ext. R&D/Employees)$_{ft}$ is the log of one plus the expenditure on external R&D per employee. Hence, it accounts both for the intensive and extensive margins of external R&D. Imp. of Foreign Tech.$_{ft}$ is binary variable equal to 1 if firm f imports licenses and technical aid from abroad at time t and 0 otherwise. MNE$_{ft}$ is a binary variable 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.

E.2 Figures

Figure E.1. TWFE Estimates

(a) MNEs and Labor Share (b) MNEs and Robots (c) Robots and Labor Share



Note: The Figure plots the estimates I obtain from equation (8) using a two-way fixed-effects estimator. The unit of observation is a firm-year pair. I cluster standard errors at the firm level. I report the estimates for $[\underline{k}, \bar{k}] = [-3, 4]$.

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