Multinationals, Robots, and the Labor Share

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July 2025

Abstract

Using a panel of Spanish manufacturing firms covering the 1990-2017 period, I document new evidence about affiliates of multinational enterprises (MNEs): after being acquired, they exhibit a higher propensity to use robots, which leads to a reduction in their labor share. These effects are identified using a matched event-study design, which accounts for selection into multinational ownership and robot adoption. The findings are consistent with a model of robot adoption with heterogeneous firms and hold even after considering other explanations for the labor share decline. The estimates imply that without MNEs, the reduction in the manufacturing labor share over the sample period would have been 6.5% smaller. Multinational-induced robot adoption explains about two-thirds of the overall impact of multinational activity on the labor share.

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

*I thank Paola Conconi and Mathieu Parenti for their guidance and support. I thank Ludovica Gazzè, David Hémous, Wolfgang Keller, Rocco Macchiavello, Glenn Magerman, Guy Michaels, Gianmarco Ottaviano, Stephen Redding, Tristan Reed, John Van Reenen, Bradley Setzler, Catherine Thomas, and José Vasquez for useful comments and seminar participants at the ECARES lunch seminar, CIE Conference, XXXV Jornadas de Economía Industrial, Young Economist Symposium, ENTER Jamboree, European Trade Study Group, RIEF Doctoral Meeting, University College of London ENTER Seminar, KIIS Workshop, XIV FIW Conference in International Economics, SIEPI Workshop 2022, and Conference on Robots and Automation 2022. The opinions expressed here are those of the author and do not necessarily reflect the position of the Bank of Italy. All errors are mine. E-mail for correspondence: fabrizioleone93@gmail.com

1 Introduction

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

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

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

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

[1] They are defined as "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.

disproportionate share of production and employment, tend to be more innovative, and are more involved in international trade than domestic firms.

I use the firm-level data to document two new facts about multinational affiliates. First, they have a lower labor share than domestic firms.[2] Second, multinational affiliates systematically exhibit a higher rate of robot adoption than domestic firms which, in turn, is associated with a lower labor share. Using the cross-country industry-level data, I show that analogous patterns also apply beyond the Spanish manufacturing sector.

These facts can be explained as the result of both selection and treatment effects by a model in which heterogeneous firms can be acquired by multinationals and choose whether to incur a sunk cost to adopt robots that reduce marginal production costs.[3] The model predicts that more productive firms are more likely to be acquired and adopt robots. If multinational ownership further enhances performance, affiliates are even more likely to adopt robots, which boosts production but reduces the labor share.

To disentangle selection from treatment effects and triangulate the relationship between multinational acquisitions, robot adoption, and labor share dynamics, I use an event-study design and proceed in two steps. First, I examine whether firms acquired by a multinational experience a drop in their labor share after the acquisition. Second, I assess whether multinational acquisitions make affiliates more likely to invest in robots, and if these investments reduce their labor share.

The effects of multinational acquisitions are identified by comparing firms that are acquired to those that remain under domestic ownership throughout.[4] To address selection into multinational ownership, I use a nearest neighbor matching algorithm to create a control group of firms that is indistinguishable from acquired ones in terms of several observable characteristics. To account for the staggered timing of acquisitions and their possible time-varying effects, I use the estimator proposed by Sun and Abraham (2021).[5] I apply a similar approach to identify the effects of robot adoption.

The estimates confirm the model prediction that multinational acquisitions reduce the labor share at the firm level through robot adoption, even after controlling for selection effects. Post acquisition, affiliates experience an average reduction in labor share of 6.5

[2] I define the labor share as the ratio of labor compensation to gross value added. However, I show that my results are robust to defining the labor share in terms of production costs.

[3] The model extends Koch et al. (2021) and Bonfiglioli et al. (2022) to model robot adoption decisions, and draws on Guadalupe et al. (2012) to model multinational acquisitions.

[4] In Section 5, I show that the baseline results are robust to using two alternative control groups: firms involved in domestic mergers and firms always owned by a multinational.

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

percentage points (15% relative to the sample average). They also increase the likelihood of adopting robots by 11 percentage points (30% relative to the sample average). Robot adoption, in turn, reduces the labor share by 2 percentage points, one-third of the total reduction observed after multinational acquisitions.[6]

An interesting question is why multinational acquisitions create incentives to invest in robots. Using again a matched event-study design, I show that multinational parents enable affiliates to expand into global markets through their networks. However, affiliates must scale up production to convert increased demand into actual sales. Adopting robots is one way to achieve this, which is consistent with the model predictions and previous work showing that foreign market access is a crucial driver of innovation (Lileeva and Trefler, 2010; Bustos, 2011; Guadalupe et al., 2012). Unlike Hicks-neutral technology, however, robots shift income away from labor.

Finally, I use the reduced-form estimates to examine how changes at the firm level contribute to shaping industry-level labor share dynamics. I consider two scenarios. In the first, I simulate how the Spanish manufacturing labor share would have evolved in the absence of multinational-induced robot adoption over the sample period. In the second, I completely turn off multinational acquisitions. The results suggest that in the absence of MNEs, the decline in the manufacturing labor share over the sample period would have been 6.5% smaller. Multinational-induced robot adoption accounts for about two-thirds of this effect. These findings offer new insights into how globalization (in the form of MNEs) and technological change (in the form of robots) interact and jointly contribute to the decline in the manufacturing labor share.

Related Literature. This paper contributes to the literature on the effects of multinational acquisitions. Prior research finds that acquired firms tend to be more productive (Griffith, 1999; Harris and Robinson, 2003; Arnold and Javorcik, 2009; Alfaro and Chen, 2018; Bircan, 2019; Fons-Rosen et al., 2021), have better access to credit (Harrison and McMillan, 2003; Desai et al., 2004; Manova et al., 2015), innovate more (Guadalupe et al., 2012), trade more (Hanson et al., 2005; Ekholm et al., 2007; Ramondo et al., 2016; Conconi et al., 2024), pay higher wages (Almeida, 2007; Heyman et al., 2007), and adopt superior management practices (Bloom et al., 2012). The literature also acknowledges that these improvements may be biased toward high-skilled labor (Feenstra and Hanson,

[6] The richness of the ESEE data allows me to control for other factors—possibly complementary to robots—identified in the literature that might contribute to labor share decline, e.g., factor-biased technological change, investment in intangibles, market power, and integration into global value chains. The negative impact of robots on the labor share persists even after accounting for these mechanisms.

1997; Aitken et al., 1996; Koch and Smolka, 2019; Setzler and Tintelnot, 2021) or capital (Sun, 2020). By showing that firms acquired by a multinational adopt robots, which in turn reduce their labor share, I highlight a new channel through which multinational acquisitions redistribute income between production factors within affiliates.

This paper also contributes to the debate on the global labor share decline. Technological change and globalization are widely recognized as key drivers of this trend (see Grossman and Oberfield, 2022, for a survey).[7] Most studies examine these factors separately, with a few exceptions. Galle and Lorentzen (2022) develop a framework to analyze the combined effects of the China shock and automation on U.S. labor markets. Faia et al. (2021) and Stapleton and Webb (2022) investigate under which conditions offshoring and automation can be complementary. Using time-series methods, Bergholt et al. (2022) identify automation as the primary driver of the U.S. labor share decline, while also accounting for other channels including rising firm markups, declining worker bargaining power, and faster investment-specific technology growth. I contribute to this literature in two ways. First, while most studies rely on aggregate data at the occupation, commuting zone, or country level, I leverage within-firm variation over time, which allows me to control for firm-specific factors that drive selection into multinational ownership and robot adoption.[8] Second, while globalization is often measured through trade exposure (e.g., import share from China), I focus on multinational acquisitions, highlighting a distinct yet complementary dimension of globalization.

Finally, this paper contributes to the literature on robot adoption. Recent studies using firm-level data show that adopters are typically large manufacturing firms (Acemoglu et al., 2020; Humlum, 2021; Koch et al., 2021; Bonfiglioli et al., 2022; Koch and Manuylov, 2023). By showing that multinational acquisitions spur robot adoption by providing affiliates access to foreign markets, I offer a new perspective on why firms invest in robots.

The paper unfolds as follows. Section 2 introduces the data. Section 3 presents new motivating facts. Section 4 outlines the model and its predictions. Section 5 contains the empirical results. Section 6 shows the counterfactuals. Section 7 concludes.

[7]Technological explanations include capital-biased technical change (Karabarbounis and Neiman, 2014), intangible and modern capital (Koh et al., 2020; Aghion et al., 2023), robots (Acemoglu et al., 2020; Koch et al., 2021; Koch and Manuylov, 2023), and other automation technology (Aghion et al., 2022). The literature also links the labor share decline to global value chain integration (Elsby et al., 2013; Leblebicioğlu and Weinberger, 2021; Panon, 2022) and multinational investment (Decreuse and Maarek, 2015; Adachi and Saito, 2020; Sun, 2020).

[8]This also applies to Stapleton and Webb (2022), who use ESEE data to study firms' offshoring and automation choices. The key difference is that I focus on Spanish firms acquired by foreign MNEs, while they analyze Spanish firms investing abroad. Additionally, I use the firm-level results to assess how affiliate-level changes shape industry-level labor share dynamics.

2 Data

This section introduces the data used in this paper. See Online 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 firm exit or missing response.

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

Sample Selection and Key Variables. Based on International Monetary Fund (2007), a firm is considered a multinational affiliate if a company headquartered outside Spain owns at least 10% of its capital.[9] 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 Investments (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.[10] Third, I exclude firms involved in domestic mergers during the sample period. The final sample consists of two types

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

[10]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.

of firms: those that are always under domestic control (i.e., "domestic firms") and those switching from domestic to multinational ownership (i.e., "multinational affiliates").[11]

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); (5) Local Area Network (LAN). Based on the response to this question, I create a binary indicator for whether a firm uses "Robotics" (system 2) in a given year.[12] 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 equal to one since the first year a firm employs a robot. So, for example, if a firm first reports the adoption of robots in 2002, the indicator switches from zero to one from that year onward. 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. Notice that while the ESEE is one of the few data sources tracking automation technology adoption over a long time span, it only allows for the study of the extensive margin of adoption. Since it lacks information on expenditures for these technologies, it cannot be used to assess changes in automation intensity within or between firms.

I define the labor share as the ratio of labor compensation to gross value added (henceforth, the value-added labor share). Labor compensation is computed as the product of average labor costs—which include salaries and social security contributions—and the number of employees. Gross value added is calculated as total sales minus expenditure on intermediate inputs. This expenditure includes labor compensation, costs of physical inputs (such as raw materials and energy), and payments for external services, and is adjusted for changes in inventories during the year.[13]

[11]While firms always owned by a multinational (greenfield FDI) and those involved in domestic mergers are excluded from the baseline sample, in Section 5 I show that my baseline results are robust to using them as alternative control groups.

[12]Even though the expression "industrial robots" is not explicitly used, Koch et al. (2021) document that robot adoption patterns in the ESEE data are consistent with the industry-level trends reported by International Federation of Robotics (2019).

[13]Defining the labor share in terms of value added is the standard practice in the literature (Elsby et al., 2013; Autor et al., 2020; Acemoglu et al., 2020; Gutiérrez and Piton, 2020; Panon, 2022). Following another strand of the literature (Doraszelski and Jaumandreu, 2018; Castro-Vincenzi and Kleinman, 2023; Koch and Manuylov, 2023; Mertens and Schoefer, 2024), I also construct an alternative measure of the labor share, defined as the ratio of labor compensation to expenditure on intermediate inputs (henceforth, the production-cost labor share). Both variables are defined as in the main text. For the remainder of the paper, I use the value-added labor share as the baseline measure, and the production-cost labor share for robustness checks. Online Figure A.1 shows that both measures exhibit very similar patterns, with a correlation of 94%, though the value-added labor share is approximately 15 percentage points lower in absolute terms.

Sample Description. The final sample spans 1990 to 2014, the last year for which robot adoption information is available, and includes 3,128 firms.[14] Among them, 102 are eventually acquired by a multinational. Online Table A.1 reports the number of acquisitions by year. Online Table A.2 shows summary statistics by ownership type, pooling together pre and post-acquisition periods for multinational affiliates. Firms acquired by a multinational 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. Online Figure A.2 shows that multinational affiliates perform better than firms that are always under domestic control already before the acquisition.

Although multinational affiliates make up only about 3% of firms in the sample each year, as shown in Online Figure A.4, they account for 25% of production, 25% of exports, 15% of employment, and 30% of capital stock. These patterns align with findings from other countries, including Belgium (Conconi et al., 2024), Indonesia (Arnold and Javorcik, 2009), Turkey (Bircan, 2019), and the United States (Antràs et al., 2022).

2.2 Industry-Level Data

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

The final dataset includes 37 middle and high-income countries and 20 industries from 2005 to 2014. Industries are agriculture, mining, 15 two-digit manufacturing sectors, electricity and water supply, and construction. Online Table A.3 shows sample summary statistics. In the next section, I use these data to provide suggestive evidence that the relationship between multinational ownership, robot adoption, and the labor share observed in the Spanish manufacturing industry may also hold in other countries and sectors.

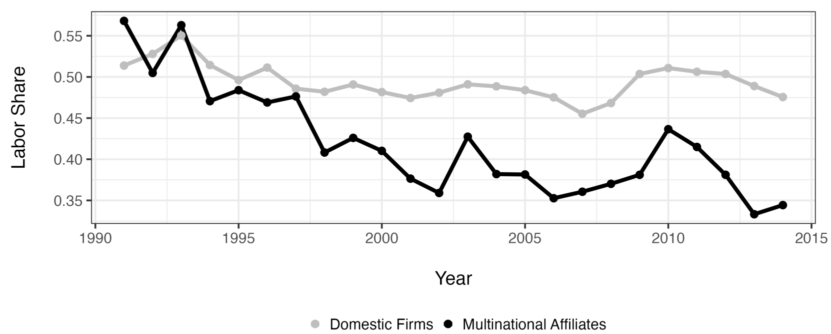
[14] Due to my sample selection criteria, no firm is owned by a multinational or adopts robots in 1990. Any acquisition or adoption event can only occur from 1991 onward. This choice is motivated by the identification strategy in Section 5, which relies on within-firm changes in ownership and robot adoption and requires observing both pre-acquisition and pre-adoption periods. This approach is consistent with previous literature (Guadalupe et al., 2012; Bircan, 2019; Koch and Smolka, 2019; Koch et al., 2021).

3 Preliminary Evidence

Using the data introduced in Section 2, this section provides preliminary evidence about the relationship between multinational ownership, robot adoption, and the labor share.

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

Figure 1. Multinational Ownership and the Labor Share



Note: The figure illustrates trends in the value-added labor share for both domestic firms and multinational affiliates. Because of my sample selection criteria, there are no firms owned by multinationals in 1990. As a result, the figure begins in 1991 and ends in 2014, the last year for which data on robot adoption is available.

Figure 1 shows that the value-added labor share declines during the sample period. However, multinational affiliates experience a sharper reduction (from 56% to 34%) than domestic firms (from 51% to 47%) and tend to have a lower labor share.[15] A natural concern is that this result may be driven entirely by differences in firm size. However, as shown in Online Figure A.5, a similar pattern holds when the group of domestic firms is split by employment level. As expected, the gap between multinational affiliates and large domestic firms is smaller than with small domestic firms. Nevertheless, the overall trend persists, suggesting that the pattern in Figure 1 holds beyond firm size.

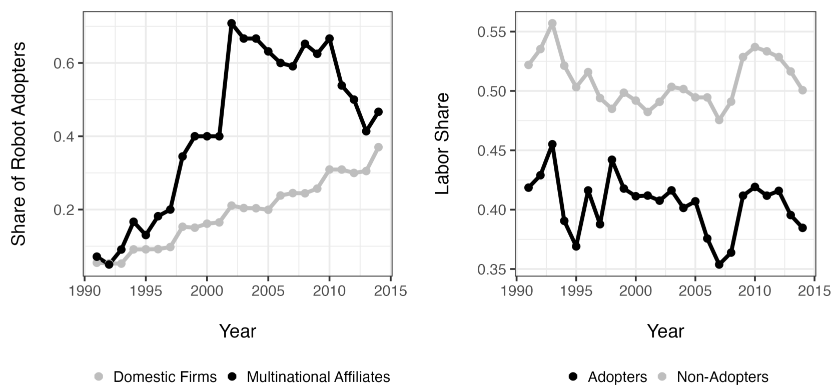
The trends in Figure 1 reflect both within-group changes in the labor share and between-group employment reallocation. In Online Appendix A.4, I use the Olley and Pakes (1996) decomposition and find that the within-group margin accounts for 73% of the total value-added labor share reduction. Therefore, understanding why multinational affiliates experience a declining labor share is crucial to explain labor share trends at the

[15] A similar pattern arises when measuring the labor share in terms of production costs, as shown in Online Figure A.3.

industry level.[16]

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

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



Note: The left panel shows the share of robot adopters among domestic firms and multinational affiliates. The right panel shows value-added labor share trends among robot-adopting firms and non-adopters. Because of my sample selection criteria, there are no firms owned by multinationals or using robots in 1990. As a result, the figure begins in 1991 and ends in 2014, the last year for which data on robot adoption is available.

The left panel of Figure 2 shows that the share of robot adopters increases during the sample period. However, multinational affiliates experience a higher total increase (from 7% to 46%) than domestic firms (from 6% to 37%) and feature a systematically higher adoption rate. Because multinational affiliates account for about 3% of all firms each year, as shown in Online Figure A.4, the left panel of Figure 2 does not merely reflect changes in sample composition—though changes in the identity of multinational affiliates over time do contribute. The right panel of Figure 2 shows that robot-adopting firms exhibit a stronger labor share reduction (from 41% to 38%) than non-adopters (from 52% to 50%) and have a lower labor share throughout the sample period.[17]

[16]Among multinational affiliates, the reallocation of market shares from high to low labor share firms explains about 52% of the decline. The within-firm component is also negative, and explains about 31% of the reduction. The contribution of entry and exit is constant. This result is consistent with Autor et al. (2020) and Panon (2022), who show that the labor share decline in the U.S. and France between the 1990s and 2000s is due to market share reallocation to "superstar firms" with low labor share. See Online Appendix A.4 for additional details about this decomposition.

[17]A similar pattern arises when measuring the labor share in terms of production costs, as shown in Online Figure A.6.

As before, one might worry that these patterns are driven by differences in firm size between groups. However, as shown in Online Figure A.7, the trends observed in Figure 2 persist even when the sample of domestic and non-adopting firms is split by employment level, suggesting that firm size does not fully account for the observed patterns.

Similarly to Figure 1, the right panel of Figure 2 subsumes both within-group changes in the labor share and between-group employment reallocation. Using again the Olley and Pakes (1996) decomposition, I find that 72% of the total labor share reduction is explained by within-group changes.

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

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

Besides the diffusion of robots, the literature highlights several additional, and potentially complementary, explanations for the decline in the labor share. These include factor-biased technological change, investment in intangible capital, process efficiency improvements, integration into global value chains, other forms of automation, and market concentration (see Grossman and Oberfield, 2022, for a summary). Leveraging the richness of the ESEE data, in Section 5 I also examine the role of these alternative mechanisms.

Beyond Spanish Manufacturing. In Online Appendix A.5, I use the cross-country industry-level panel introduced in Section 2.2 to provide suggestive evidence that Facts 1 and 2 are not unique to the Spanish manufacturing industry. After controlling for country-by-industry and time fixed effects, I show that multinational production is negatively correlated with the value-added labor share and positively correlated with the number of robots per thousand employees, a standard measure of robot diffusion (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020). Additionally, the number of robots per thousand employees is negatively correlated with the value-added labor share. These findings suggest that the patterns highlighted in Figures 1 and 2 may apply to a broad set of countries and sectors. See Online Appendix A.5 for more details.

4 Conceptual Framework

This section provides a simple model of robot adoption with heterogeneous firms. The model is consistent with the facts in Section 3 and guides the analysis in Section 5.

Scope and Relationship with the Literature. Building on Koch et al. (2021) and Bonfiglioli et al. (2022), the model incorporates firm heterogeneity à la Melitz (2003) within a task-based framework of robot adoption à la Acemoglu and Restrepo (2018). However, while those papers exclusively attribute firm heterogeneity to productivity, I also account for differences in appeal to consumers and cost structures, for which the ESEE data allows me to construct proxies. Firms can be owned by a multinational, and I model firm selection into multinational ownership building upon Guadalupe et al. (2012). Since the model is fairly standard and primarily serves to organize the empirical analysis, I outline its key features below and refer to Online Appendix B for additional details.

Environment and Predictions. The economy consists of a large number of heterogeneous firms living for an infinite sequence of periods. Within each period, events unfold as follows. First, firms may be acquired by a multinational; once acquired, they remain under multinational ownership forever. Second, firms decide whether to adopt robots, a choice that, once made, is irreversible.[18] Finally, firms produce and sell their output. Firms take input prices as given and carry out a unit measure of tasks using machines or labor to produce output. Firms compete monopolistically in the output market.

Firms are heterogeneous along four dimensions: (1) total factor productivity, (2) appeal to consumers, (3) sunk robot adoption costs, and (4) cost of being acquired by a multinational. Multinational acquisitions can improve firm performance along the first three dimensions. Robot adoption requires paying a sunk cost, but reduces marginal costs by expanding the set of tasks that can be performed by machines versus labor.

The model delivers three predictions. First, better-performing firms are more likely to be acquired by a multinational and adopt robots. Second, to the extent that multinational acquisitions improve firm performance, multinational affiliates are more likely to adopt robots. Finally, while robot adoption can lead to higher wages and employment, it reduces the labor share at the firm level.

These predictions are consistent with Figures 1 and 2 and rationalize them as the result of both selection and treatment effects, which are disentangled in the next section.

[18] The assumption that multinational acquisitions and robot adoption choices are irreversible is consistent with the variable definitions in Section 2.1 and the analysis in Sections 5 and 6.

5 Empirical Analysis

Building on the conceptual framework in Section 4, this section first shows that firms acquired by MNEs experience a decline in labor share compared to similar domestic firms. It then provides evidence that a key driver of this decline is their higher propensity to adopt robots. Finally, it examines other channels driving the labor share decline, why affiliates adopt robots, and additional organizational changes triggered by the acquisition.

5.1 Multinationals and the Labor Share

Empirical Strategy. Using the methodology proposed by Sun and Abraham (2021), I estimate the following baseline equation:

$$y_{ft} = \sum_{g \in \mathcal{G}} \sum_{s=-\underline{k}}^{\bar{k}} \beta_{g,s} \mathbf{1}\{f \in g\} MNE_{ft}^{s} + \alpha_f + \alpha_t + \varepsilon_{ft}. \tag{1}$$

y_{ft} is the outcome of interest of firm f in year t. A cohort $g \in \mathcal{G}$ is a set of firms acquired in the same year. The indicator function $\mathbf{1}\{f \in g\}$ takes a value of one if firm f belongs to cohort g. MNE_{ft}^{s} is a binary indicator that identifies the years before or after firm f is acquired by a multinational. $\underline{k}$ and $\bar{k}$ denote the first and last period for which MNE_{ft}^{s} can be defined. α_f and α_t are firm and year-level fixed effects, while ε_{ft} is the error term. Firms that remain under domestic ownership throughout serve as the control group. Therefore, the coefficients $\beta_{g,s}$ measure cohort-year-specific treatment effects that multinational acquisitions have on firms acquired in a given year compared to never acquired ones. I normalize $\beta_{g,-1} = 0$ for all cohorts, which means that all other estimated coefficients are relative to the year before the acquisition. Cohort-year-specific treatment effects can then be aggregated either at the event level or into a single average effect using the size of each cohort as a weight. I cluster standard errors by firm.

Estimating equation (1) using the estimator proposed by Sun and Abraham (2021) rather than a standard two-way fixed-effects (TWFE) estimator allows me to identify the effects of multinational acquisitions on firm-level outcomes accounting for the fact that firms are acquired in different years—i.e., treatment is staggered, as shown in Online Table A.1—and that acquisition effects may evolve over time. The TWFE estimator fails to do so because already treated units enter the control group for some cohorts, generating a "forbidden comparison" that may bias the estimates (Borusyak et al., 2024).

A challenge when estimating equation (1) is that better-performing firms self-select into multinational ownership, as shown in Section 2.1 and predicted by the model in Section 4. Absent exogenous variation in firms' corporate structure, I build upon previous literature and use a matching algorithm to identify treatment effects beyond selection (Arnold and Javorcik, 2009; Guadalupe et al., 2012; Koch and Smolka, 2019). The purpose of this procedure is to create a group of domestic firms that is indistinguishable from those that are acquired in terms of several observable characteristics. The identification assumption is that, after matching and conditional on the fixed effects, never acquired firms are a credible counterfactual for acquired ones.

I proceed in two steps. First, using a nearest neighbor algorithm, I match each acquired firm to the most similar five domestic firms in terms of observable characteristics in trends (to account for differences in growth) and levels (to account for differences in size).[19] Firms are matched based on their sales growth rate, level of sales, value added, employment, labor costs, investment, fixed assets, R&D expenditure, export values, number of export destinations, and value-added labor share. All variables refer to the year before the acquisition and, except for the sales growth rate and the value-added labor share, are in logarithms. In the second step, I estimate equation (1) on the matched sample.

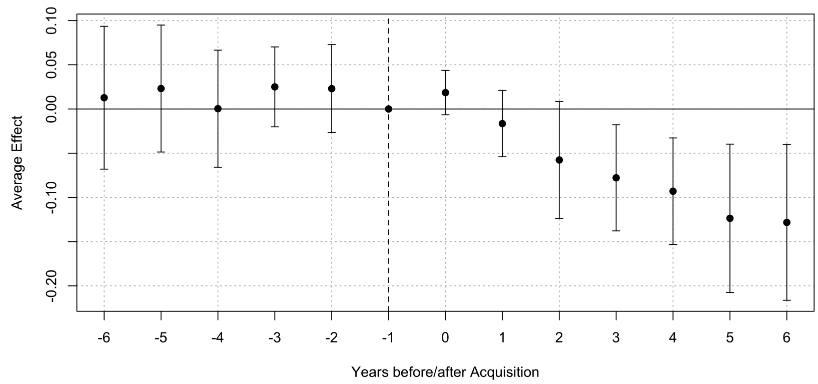
The matched sample includes all the original 102 multinational affiliates and 255 domestic firms. Online Table A.4 shows the average characteristics for the two groups before and after matching. Before matching, there are economically sizable average differences between the two groups. After matching, the two groups are indistinguishable in terms of growth, level of domestic activities, investment patterns, value-added labor share, and international trade participation.

Baseline Results. I estimate equation (1) using the value-added labor share as the outcome variable. Figure 3 shows a progressive decline in the value-added labor share following multinational acquisitions. The absence of significant pre-trends suggests parallel value-added labor share trajectories between groups in the absence of the acquisition.

Column (1) of Table 1 indicates that the average value-added labor share reduction is about 6.5 percentage points, a 15% decrease relative to the mean value-added labor share in the matched sample. Columns (2) to (4) of Table 1 decompose the value-added labor share into its components: (the log of) number of employees, labor costs, and gross value added. Wages do not significantly increase. Although acquired firms employ more workers after the acquisition (11%), value added rises disproportionately more (21%),

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

Figure 3. Multinational Acquisitions and Labor Share Dynamics



Note: The figure plots the estimates I obtain from equation (1) using the value-added labor share as the dependent variable. Cohort-year-specific treatment effects are aggregated at the event level using the size of each cohort as a weight. The unit of observation is a firm-year pair. There are 4,029 observations. Firms are matched using a one-to-five nearest neighbor matching algorithm based on the variables in Online Table A.4. I cluster standard errors at the firm level and report 95% confidence intervals. Estimates are shown for the period spanning six years before to six years after the acquisition.

driving the value-added labor share decline. Online Table A.5 replicates Table 1 on the unmatched sample. As expected, the estimated coefficients are larger in magnitude than those obtained after matching.

Table 1. Multinational Acquisitions and the Labor Share

Dependent Variables:	Labor Share$_{ft}$	Log(Employees)$_{ft}$	Log(Wages)$_{ft}$	Log(Value Added)$_{ft}$
	(1)	(2)	(3)	(4)
MNE$_{ft}$	-0.065***	0.110**	0.034	0.215***
	(0.021)	(0.048)	(0.023)	(0.074)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Matched Sample	Yes	Yes	Yes	Yes
Observations	4,029	4,029	4,029	4,029

Note: The table shows the estimates of equation (1). Cohort-year-specific treatment effects are aggregated into a single (pooled) estimate using the size of each cohort as a weight. The unit of observation is a firm-year pair. In column (1), the dependent variable is the value-added labor share of firm f in year t. In column (2), the dependent variable is Log(Employees)$_{ft}$, which is the log of the number of employees of firm f in year t. In column (3), the dependent variable is Log(Wages)$_{ft}$, which is the log of gross labor costs incurred by firm f in year t. In column (4), the dependent variable is Log(Value Added)$_{ft}$, which is the log of gross value added of firm f in year t. MNE$_{ft}$ is a binary indicator equal to one if firm f is multinational-owned in year t and zero otherwise. Firms are matched using a one-to-five nearest neighbor matching algorithm based on the variables in Online Table A.4. Cluster standard errors at the firm level in parentheses. Significance levels: *** 0.01, ** 0.05, * 0.1.

Robustness to Alternative Specifications. The results in Figure 3 are robust to several alternative specifications. Online Figure A.8 demonstrates that the findings hold when replacing year fixed effects with industry-by-year fixed effects, which account for common changes within the same NACE 2 sector. Online Figure A.9 confirms the robustness of the baseline results using a one-to-three nearest neighbor matching algorithm. Online Figure A.10 shows that the results are robust to using the production-cost labor share as the outcome variable. Finally, Online Figure A.11 shows that excluding firms acquired in 1991 and 1992 does not affect the results, indicating that the baseline results are not driven by the higher acquisition rate in those years, as shown in Online Table A.1.

Robustness to Using Domestic Mergers as the Control Group. Although the results in Figure 3 are based on a matched sample and show no evidence of pre-trends, concerns may remain that unobserved shocks influencing both acquisitions and labor share dynamics make firms that stay under domestic ownership a poor counterfactual for multinational affiliates. To address this, I follow Fons-Rosen et al. (2021) and compare firms acquired by multinationals with a matched group of firms acquired by domestic parents. The key identification assumption is that, after matching and conditional on fixed effects, the assignment of a domestic or foreign parent is as good as random, which is weaker than assuming that the acquisition itself is (conditionally) random.

To identify firms involved in domestic mergers, I use a variable in the ESEE data that records organizational changes. The six possible scenarios include: (1) the firm has split, (2) the firm has acquired other firms, (3) the firm was established through a split, (4) the firm resulted from a merger (i.e., it was acquired by another domestic firm), (5) the firm has changed its trademark or legal form, and (6) the firm has not experienced any organizational changes.

In the baseline analysis, the control group consists of firms in category (6). For this robustness check, I modify it to include only firms in category (4), which are tracked in the ESEE data both before and after the merger. Firms are matched using the same algorithm and variables as in the baseline specification. The robustness (matched) sample includes 102 treated firms and 260 control firms. Online Table A.6 shows that treated firms outperform control firms before the acquisition. However, these differences vanish after matching. Online Figure A.12 shows that the patterns in Figure 3 hold when using domestic mergers as the control group, suggesting that it is the multinational nature of the acquisition, more than the acquisition itself, that drives the labor share decline.

Robustness to Using Greenfield FDI as the Control Group. Another interesting comparison involves using firms that are always multinational-owned as the control group. This comparison helps determine whether brownfield FDI leads to different labor share dynamics than greenfield FDI.

I replace the original control group of always domestic-owned firms with one consisting of firms always owned by a multinational. This new control group includes two types of firms: those already owned by a multinational in 1990 (the first year of the sample, for which the acquisition year cannot be identified) and those born under foreign ownership after 1990. No control firm switches to domestic ownership during the sample period.

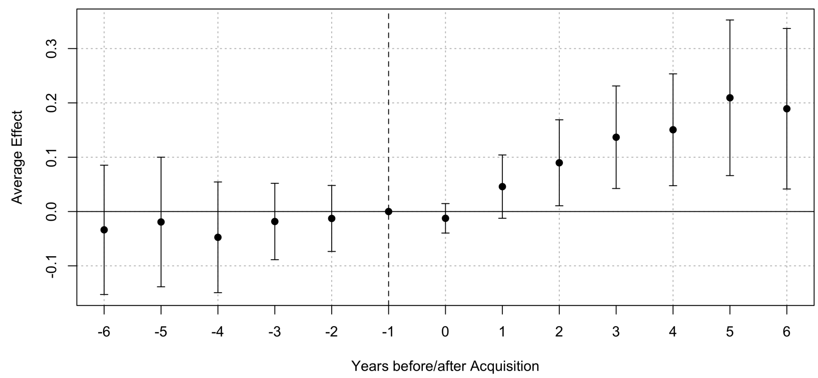
Firms are matched using the same algorithm and variables as in the baseline specification. The robustness (matched) sample includes 102 treated firms and 127 control firms. Online Table A.7 shows the average characteristics for both groups before and after matching. Consistent with Takayama (2023), I find that firms always owned by multinationals tend to outperform future affiliates before the acquisition, though these differences disappear after matching. Online Figure A.13 shows that the patterns in Figure 3 hold when using greenfield FDI as the control group, suggesting that the acquisition event induces substantial changes within acquired firms.

5.2 Mechanism: The Role of Robots

Overall Approach. The conceptual framework in Section 4 suggests that multinational acquisitions, by enhancing firm performance, may make affiliates more likely to invest in robots, which in turn reduces their labor share. To triangulate the relationship between multinational acquisitions, robot adoption, and labor share dynamics, I proceed in two steps. First, I document that multinational acquisitions make firms more likely to invest in robots. Second, I show that robot adoption leads to a decline in the labor share.

Multinationals and Robots. To test if multinational acquisitions spur investment in robots, I estimate equation (1) using a binary indicator equal to one since the first year firm f adopts a robot as the outcome variable. Figure 4 indicates that the probability of adopting robots gradually increases after the acquisition. The absence of significant pre-trends suggests parallel robot adoption trajectories between groups in the absence of the acquisition. Column (1) of Table 2 shows that the average increase in the probability of adopting robots is about 11 percentage points, a 30% increase relative to the unconditional probability in the matched sample. Column (2) indicates that the estimates on the unmatched sample are larger in absolute value than those obtained after matching.

Figure 4. Multinational Acquisitions and Robot Adoption Dynamics



Note: The figure plots the estimates I obtain from equation (1) using a binary indicator equal to one since the first year a firm adopts a robot as the outcome variable. Cohort-year-specific treatment effects are aggregated at the event level using the size of each cohort as a weight. The unit of observation is a firm-year pair. There are 4,029 observations. Firms are matched using a one-to-five nearest neighbor matching algorithm based on the variables in Online Table A.4. I cluster standard errors at the firm level and report 95% confidence intervals. Estimates are shown for the period spanning six years before to six years after the acquisition.

Table 2. Multinational Acquisitions and Robot Adoption

Dependent Variable:	Robot Adoption$_{ft}$ (1)	(2)
MNE$_{ft}$	0.115***	0.171***
	(0.031)	(0.031)
Firm FE	Yes	Yes
Year FE	Yes	Yes
Matched Sample	Yes	No
Observations	4,029	24,106

Note: The table shows the estimates of equation (1). Cohort-year-specific treatment effects are aggregated into a single (pooled) estimate using the size of each cohort as a weight. The unit of observation is a firm-year pair. The dependent variable is a binary indicator equal to one since the first year firm f uses a robot. MNE$_{ft}$ is a binary indicator equal to one if firm f is multinational-owned in year t and zero otherwise. In column (1), firms are matched using a one-to-five nearest neighbor matching algorithm based on the variables in Online Table A.4. Cluster standard errors at the firm level in parentheses. Significance levels: *** 0.01, ** 0.05, * 0.1.

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

$$y_{ft} = \sum_{j \in \mathcal{J}} \sum_{s=-\underline{k}}^{\bar{k}} \beta_{g,s} \mathbf{1}\{f \in j\} R^s_{ft} + \alpha_f + \alpha_t + \varepsilon_{ft}. \quad (2)$$

The notation follows from equation (1), with two key differences: a cohort $j \in \mathcal{J}$ now represents a set of firms that employ robots for the first time in the same year, and MNE^s_{ft} is replaced by R^s_{ft}, a binary indicator that identifies the years before or after firm f adopts its first robot. As before, I estimate equation (2) using the method proposed by Sun and Abraham (2021) and then average cohort-year-specific treatment effects at the event level or into a single average effect using the size of each cohort as a weight.

To account for firm self-selection into robot adoption, I again use a one-to-five nearest neighbor matching algorithm. Firms are matched based on the same observable characteristics as in Online Table A.4. However, since Figure 4 shows that multinational acquisitions increase the likelihood of affiliates adopting robots, I perform matching conditional on ownership status. Specifically, I match robot-adopting multinational affiliates with non-adopting multinational affiliates and robot-adopting domestic firms with non-adopting domestic firms. Matching conditional on ownership is crucial: without it, robot adopters could differ from non-adopters on unobservable factors related to multinational ownership. Once matched, groups are combined into a single estimation sample.

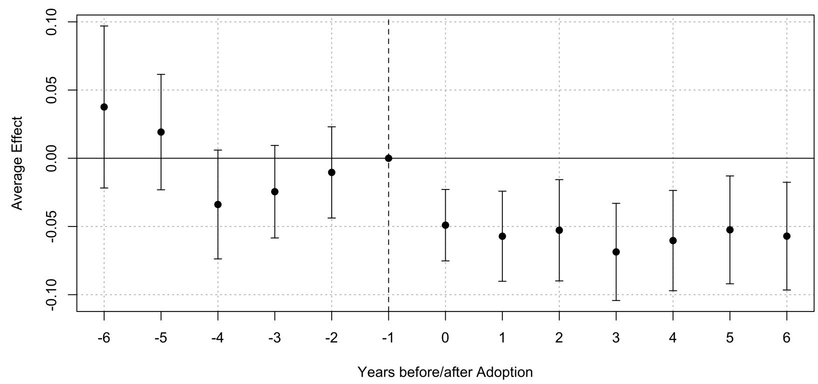
The identification assumption is that, after matching and conditional on the fixed effects, firms that never adopt robots are a credible counterfactual for those that do adopt robots. The matched sample includes 935 non-adopters and 376 adopters. Online Table A.8 shows that matching makes the two groups indistinguishable.

I estimate equation (2) using the value-added labor share as the outcome variable. Figure 5 shows that the value-added labor share permanently decreases after the adoption of robots. The absence of significant pre-trends suggests parallel value-added labor share trajectories between groups in the absence of the adoption. Column (1) of Table 3 indicates that the average reduction in value-added labor share is about 2.2 percentage points, a 11% decrease relative to the mean value-added labor share in the matched sample.[20] This number is about one-third of the overall effect documented in the first column of Table 1. Column (2) of Table 3 shows that the results on the unmatched sample are

[20] This finding is consistent with Koch and Manuylov (2023), who, using the ESEE data and building upon the framework of Doraszelski and Jaumandreu (2018), document that robot adoption drives firm-level labor-augmenting technological change, thereby reducing the Spanish manufacturing labor share.

slightly larger in absolute value than those obtained after matches are established.

Figure 5. Robot Adoption and Labor Share Dynamics



Note: The figure plots the estimates I obtain from equation (2) using the value-added labor share as the outcome variable. Cohort-year-specific treatment effects are aggregated at the event level using the size of each cohort as a weight. The unit of observation is a firm-year pair. There are 14,781 observations. Firms are matched using a one-to-five nearest neighbor matching algorithm based on the variables in Online Table A.8. I cluster standard errors at the firm level and report 95% confidence intervals. Estimates are shown for the period spanning six years before to six years after the acquisition.

Table 3. Robot Adoption and the Labor Share

Dependent Variable:	Labor Share$_{ft}$	
	(1)	(2)
Robot Adoption$_{ft}$	-0.022**	-0.026***
	(0.011)	(0.010)
Firm FE	Yes	Yes
Year FE	Yes	Yes
Matched Sample	Yes	No
Observations	14,781	24,096

Note: The table shows the estimates of equation (2). Cohort-year-specific treatment effects are aggregated into a single (pooled) estimate using the size of each cohort as a weight. The unit of observation is a firm-year pair. The dependent variable is the value-added labor share of firm f in year t. Robot Adoption$_{ft}$ is a binary indicator equal to one since the first year firm f uses a robot. Firms are matched using a one-to-five nearest neighbor matching algorithm based on the variables in Online Table A.8. Cluster standard errors at the firm level in parentheses. Significance levels: *** 0.01, ** 0.05, * 0.1.

Robustness. The results in Figure 4 are robust to several alternative specifications. Online Figure A.14 shows that they hold when replacing year fixed effects with industry-by-year fixed effects, which account for common changes within the same NACE 2 sector. Online Figure A.15 confirms the robustness of the results using a one-to-three nearest neighbor matching algorithm. Online Figure A.16 shows that excluding firms acquired in 1991 and 1992 does not affect the results. Despite this evidence, similarly to Section 5.1, concerns may still persist regarding the suitability of domestic firms as a counterfactual for acquired firms. To address these concerns, I adopt the same approach as in Section 5.1 and use domestic mergers and greenfield FDI as alternative control groups. As shown in Online Figures A.17 and A.18, the results in Figure 4 are robust when these alternative control groups are used. Finally, Online Figure A.19 shows that the findings in Figure 5 hold even when using the production-cost labor share as the outcome variable.

5.3 Comparison with Other Mechanisms

Mechanisms Discussion. Robot adoption may not be the only channel through which multinational acquisitions induce a labor share decline. Other—possibly complementary—mechanisms highlighted by the literature are factor-biased technological change (Karabarbounis and Neiman, 2014), investment in intangible capital (Koh et al., 2020), integration into global value chains (Elsby et al., 2013; Panon, 2022), process efficiency improvements (Aghion et al., 2023), other forms of automation (Aghion et al., 2022), and market concentration (Autor et al., 2020).[21]

The richness of the ESEE data allows me to construct proxies for these mechanisms and assess their relationship with the labor share. I proxy factor-biased technological change with the ratio of fixed assets to employees and investment in intangible capital with total R&D expenses. Integration into global value chains is measured using two indicators: the ratio of intermediate input expenditures (including imports) to value added for import-side integration and the ratio of export revenues to total sales for export-side integration. Process efficiency is captured by a binary indicator equal to one if firms produce standardized products. Other forms of automation are proxied by a binary indicator for the use of computer-assisted design (CAD), numerically controlled machines (CNC), or flexible manufacturing systems.[22] I proxy firm market power using firm-level

[21]For example, Stapleton and Webb (2022) use ESEE data to show that robot adoption and offshoring jointly reduce the labor share at the firm level. Additionally, Bergholt et al. (2022) find that automation, market power, and factor-specific technological change drive the U.S. labor share decline.

[22]This indicator is based on the survey question about automation investment described in Section 2.1.

markups estimated with the method of De Loecker and Warzynski (2012).

Empirical Specification and Results. To examine the role of each channel, I proceed as follows. First, I regress firm f's value-added labor share in year t on a binary indicator for multinational ownership. I then sequentially introduce a binary indicator for robot adoption and the other control variables. Comparing coefficients across specifications helps assess the contribution of each channel. All regressions use the matched sample from Figures 3 and 4, include firm and year fixed effects, and report standard errors clustered by firm. Since the estimator proposed by Sun and Abraham (2021) does not accommodate multiple treatments, I instead use a standard TWFE estimator for this analysis. Table 4 shows the estimation results.

Table 4. Comparing Mechanisms for the Falling Labor Share

Dependent Variable:	Labor Share$_{ft}$								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
MNE$_{ft}$	-0.067**	-0.062**	-0.063**	-0.065**	-0.061**	-0.061**	-0.060**	-0.059**	-0.047**
	(0.029)	(0.028)	(0.028)	(0.028)	(0.026)	(0.027)	(0.027)	(0.026)	(0.023)
Robot Adoption$_{ft}$		-0.038**	-0.037**	-0.036*	-0.032*	-0.032*	-0.033*	-0.034*	-0.031*
		(0.019)	(0.019)	(0.019)	(0.018)	(0.018)	(0.018)	(0.018)	(0.016)
Z - Log(Fixed Assets/Employees)$_{ft}$			-0.020*	-0.019*	-0.025**	-0.025**	-0.025**	-0.024**	-0.017**
			(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.008)
Z - Log(R&D Expenses)$_{ft}$				-0.010	-0.009	-0.009	-0.009	-0.009	-0.007
				(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)
Z - Log(Int. Inputs/Value Added)$_{ft}$					-0.058***	-0.057***	-0.057***	-0.057***	-0.070***
					(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Z - Log(Export/Sales)$_{ft}$						-0.010	-0.010	-0.010	-0.009
						(0.010)	(0.010)	(0.010)	(0.009)
Product Standardization$_{ft}$							-0.013	-0.013	-0.010
							(0.013)	(0.013)	(0.012)
Automation$_{ft}$								-0.019	-0.020
								(0.017)	(0.015)
Z - Log(Markup$_{ft}$)									-0.069***
									(0.006)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Matched Sample	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,029	4,029	4,029	4,029	4,029	4,029	4,029	4,029	4,029

Note: The table shows the estimates obtained from a regression of the value-added labor share of firm f in year t on firms' characteristics. The unit of observation is a firm-year pair. MNE$_{ft}$ is a binary indicator equal to one if firm f is multinational-owned in year t and zero otherwise. Robot Adoption$_{ft}$ is a binary indicator equal to one since the first year firm f uses a robot. Z - Log(Fixed Assets / Employees)$_{ft}$ is the standardized log of fixed assets per employee of firm f in year t. Z - Log(R&D Expenses)$_{ft}$ is the standardized log of total R&D expenses of firm f in year t. Z - Log(Int. Inputs/Value Added)$_{ft}$ is the standardized log of expenditure on intermediate inputs over gross value added of firm f in year t. Z - Log(Export / Sales)$_{ft}$ is the standardized log of the ratio of export sales over total sales of firm f in year t. Product Standardization$_{ft}$ is a binary indicator equal to one if firm f adopts product standardization in year t. Automation$_{ft}$ is a binary indicator equal to one if firm f uses computer-assisted design (CAD), numerically controlled machines (CNC), or flexible manufacturing systems in year t. Z - Log(Markup)$_{ft}$ is the standardized log of the markup of firm f in year t computed using the method of De Loecker and Warzynski (2012). Firms are matched using a one-to-five nearest neighbor matching algorithm based on the variables in Online Table A.4. Cluster standard errors at the firm level in parentheses. Significance levels: *** 0.01, ** 0.05, * 0.1.

Comparing the first two columns reveals that controlling for robot adoption reduces the impact of multinational ownership on the labor share by approximately 7%. Quantitatively, the coefficient on robot adoption is about two-thirds the size of the coefficient on multinational ownership. This pattern persists even after adding the other control variables, as shown in columns (3) to (9), reinforcing the idea that robot adoption mediates the labor share decline following acquisitions.

Column (9) indicates that while all candidate mechanisms are negatively correlated with the value-added labor share, only factor-biased technological change, integration into global value chains (on the import side), and market power significantly contribute to its decline. Notably, other forms of automation beyond robots do not exhibit a significant correlation with the labor share, suggesting that robots play a specific role in shaping labor share dynamics in the Spanish manufacturing industry—a finding consistent with Koch and Manuylov (2023). Among all mechanisms, robot adoption, global value chain integration, and market power exhibit the strongest negative correlation.

5.4 Why do Multinationals Adopt Robots?

Hypotheses. The results presented so far show that multinational acquisitions make firms more likely to adopt robots, which reduces their labor share. In this section, I shed light on the reasons why multinational acquisitions spur robot adoption in the first place.

According to the conceptual framework in Section 4, robot adoption entails a trade-off between sunk and marginal costs. Firms with higher productivity or demand, or lower adoption costs, are more likely to make this investment. Multinational acquisitions may make firms adopt robots due to improvements along each of these dimensions.

For instance, firms acquired by a multinational may learn superior management practices that boost their productivity (Bloom et al., 2012) and gain increased access to foreign markets via their parents (Guadalupe et al., 2012; Conconi et al., 2024). Multinational parents may also reduce affiliates' investment costs, including in robots, by alleviating their credit constraints (Harrison and McMillan, 2003; Desai et al., 2004; Manova et al., 2015) or transferring them technological knowledge (Branstetter et al., 2006; Keller and Yeaple, 2013; Gumpert, 2018; Bilir and Morales, 2020). The richness of the ESEE data allows me to distinguish among these hypotheses.

Testing the Hypotheses. To test if multinational acquisitions boost firm productivity, I inspect changes in firms' value added in production. To evaluate if multinational parents grant access to global markets to their affiliates, I exploit a survey question asking firms how they access export markets, if at all. The possible answers are that they export via their multinational parents (either using their distribution channel or directly selling to them), own means, specialized intermediaries, collective actions, or other means. To infer if acquired firms face lower investment costs, I test whether they increase external R&D expenditures per worker, an activity subject to credit constraints (Brown et al., 2012), or purchase licenses and technical aid from abroad, possibly from their parents, which I use to proxy technology transfers. Following the approach of Section 5.2, I proceed in two steps. First, I test if multinational takeovers lead to changes in any of these variables. Second, I assess the explanatory power of each channel for robot adoption. In both steps, I use the same matched sample as in equation (1).

Results. Online Table A.9 shows the pooled estimates across all cohorts and post-acquisition periods. Multinational acquisitions make firms more likely to export via their foreign parents and more productive. Their sales and export values increase accordingly, as shown in Online Table A.10. There is no evidence that affiliates increase external R&D per employee and imports of foreign technology, dismissing the investment cost channel.

Online Table A.11 indicates that only the ability to export via the parental network has a statistically significant explanatory power for robot adoption. This results is consistent with previous work showing that foreign market access is a crucial driver of innovation (Lileeva and Trefler, 2010; Bustos, 2011; Guadalupe et al., 2012).

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

Other Changes in the Production Process. A key feature of robots is their ability to perform complex tasks continuously without human supervision (International Federation of Robotics, 2021). So it plausible that their adoption coincides with a shift toward large-scale, automated production. Online Table A.12 supports this hypothesis: post-acquisition, affiliates are about 9 percentage points more likely to engage in continuous manufacturing—a 24/7, large-scale production method that relies on automated production lines. This represents a 60% increase relative to the unconditional mean in the matched sample. These findings support the hypothesis introduced in Section 4 that multinational acquisitions scale up firm operations. While robots are one channel, broader complementary changes in production can also take place.

6 Industry-Level Dynamics

Section 5 shows that after being acquired by a multinational, affiliates are more likely to adopt robots, reducing their value-added labor share. However, because these effects are identified using within-firm variation, they do not reveal how affiliate-level changes influence industry-level labor share dynamics. In this section, I aggregate the reduced-form estimates from Section 5 to evaluate the impact of multinational ownership and robot adoption on the value-added labor share in Spanish manufacturing.

Implementation. Consider the following pooled version of equation (1):

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

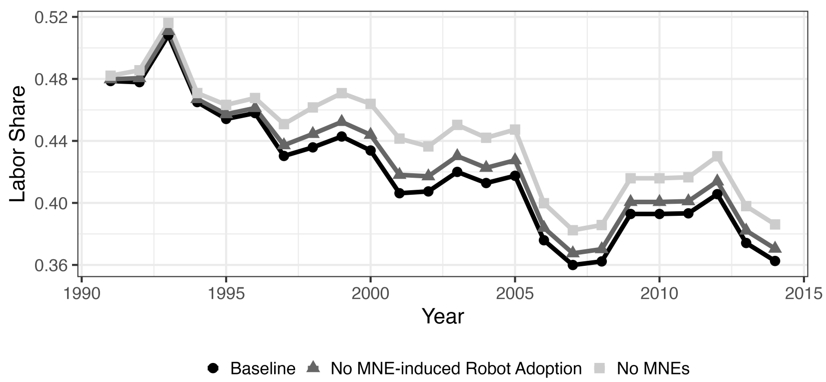
LS_{ft} is the value-added labor share of firm f in year t. The remaining notation follows from equation (1). This equation describes how multinational acquisitions affect the labor share at the firm level. Simulating it forward while shutting down the contribution of multinational ownership delivers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

I examine two scenarios. In the first, I shut down the impact of multinational acquisitions on the value-added labor share through robot adoption. This is done by discounting the estimated $\widehat{\beta}_1$ and $\widehat{\alpha}_f$ for multinational affiliates by the coefficient in column (1) of Table 2, which is the (pooled) robot adoption premium of multinational affiliates. In the second, I completely shut down the impact of multinational acquisitions on the value-added labor share by setting $MNE_{ft} = 0$ and discounting the estimated $\widehat{\alpha}_f$ for multinational affiliates accordingly. For each counterfactual scenario, I simulate value-added labor share changes using 1,000 bootstrap replications from the empirical distribution of $\widehat{u}_{ft}$ and report the average outcome across replications. See Online Appendix A.6 for more details.

Results. Figure 6 shows the results. There are two takeaways. First, without MNEs, the decline in the manufacturing labor share from 1990 to 2014 would have been 6.5% (2 percentage points) smaller. Second, multinational-induced robot adoption explains about two-thirds of the overall impact of multinational activity on the labor share.

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

Figure 6. Counterfactual Labor Share Dynamics



Note: The figure shows industry-level value-added labor share paths under three scenarios. The black line is the actual path. The dark gray line shows the counterfactual path absent multinational-induced robot adoption. The light gray line shows the counterfactual path absent multinationals enterprises. In each scenario, firm-level labor shares are aggregated using observed employment shares. Because of my sample selection criteria, there are no firms owned by multinationals in 1990. As a result, the figure begins in 1991 and ends in 2014, the last year for which data on robot adoption is available.

7 Conclusions

Using rich firm-level data for Spanish manufacturing, this paper provides evidence that multinational acquisitions make firms more likely to adopt robots. While this allows affiliates to scale up operations, it also leads to a reduction in their labor share. These findings are established after accounting for firm self-selection into both multinational acquisitions and robot adoption, are consistent with a model of robot adoption with heterogeneous firms, and hold even after considering other explanations for the labor share decline. The estimates imply that without multinationals, the drop in the industry-level labor share would have been 6.5% smaller by the end of the sample period. Multinational-induced robot adoption accounts for about two-thirds of this change.

Recent literature shows that automation, especially robots, affects not only labor markets but also areas like trade (Artuc et al., 2018), public finance (Freeman, 2015), and elections (Anelli et al., 2019). The distributional effects of multinational-induced robot adoption documented in this paper may thus be a lower bound of broader economic impacts. Exploring these wider implications is a promising avenue for future research.

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Online Appendix

"Multinationals, Robots, and the Labor Share"

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A Empirical Appendix

A.1 Additional Tables and Figures

Online Table A.1. Multinational Acquisitions by Year

Year	Number of New Acquisitions
1991	14
1992	11
1993	5
1994	1
1995	8
1996	4
1997	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 Spanish firms acquired by a foreign multinational enterprise in each year.

Online Table A.2. Summary Statistics (ESEE Data)

	Domestic		Multinational	
	Mean	St. Dev.	Mean	St. Dev.
Panel A: Automation Technology				
Robot	0.15	0.36	0.28	0.45
Numerically Controlled Machines	0.37	0.48	0.52	0.50
CAD Manufacturing	0.26	0.44	0.38	0.49
Flexible Systems	0.23	0.42	0.39	0.49
Panel B: Type of Manufacturing				
Batch Manufacturing	0.52	0.50	0.25	0.44
Mass Manufacturing	0.34	0.47	0.54	0.50
Continuous Manufacturing	0.10	0.31	0.17	0.38
Mixed Manufacturing	0.04	0.19	0.03	0.18
Panel C: Innovation and Research and Development				
Investment	0.28	1.41	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 (Cost)	0.63	0.27	0.57	0.25
Labor Share (Value Added)	0.50	0.31	0.43	0.28
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
Price Index	1.00	0.06	0.99	0.06

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

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

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

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

Online Table A.4. Goodness of Fit - Multinational Acquisitions

	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	16.80	0.16	0.98
Lag Log Value Added	15.61	13.55	15.66	0.19	0.98
Lag Log Employment	5.20	3.42	5.20	0.17	1.00
Lag Log Labor Costs	3.25	3.04	3.25	0.61	0.99
Lag Log Investment	11.84	7.70	11.91	0.34	0.99
Lag Log Fixed Assets	15.79	13.37	15.82	0.21	0.99
Lag Log RD Expenditure	6.91	1.95	6.78	0.45	0.98
Lag Log Exports	11.38	5.74	11.58	0.40	0.98
Lag Log Number of Export Markets	0.52	0.25	0.53	0.63	0.98
Lag Labor Share	0.41	0.50	0.39	0.73	0.96

Note: The table shows the goodness of fit of the one-to-five nearest neighbor matching algorithm when comparing firms acquired by a multinational (treated) to those staying under domestic ownership (control). 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. All averages refer to the year before the treatment onset. 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.

Online Table A.5. Multinational Acquisitions and the Labor Share (No Matching)

Dependent Variables:	Labor Share$_{ft}$	Log(Employees)$_{ft}$	Log(Wages)$_{ft}$	Log(Value Added)$_{ft}$
	(1)	(2)	(3)	(4)
MNE$_{ft}$	-0.084***	0.130***	0.034	0.266***
	(0.018)	(0.043)	(0.022)	(0.065)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Matched Sample	No	No	No	No
Observations	24,106	24,106	24,106	24,106

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

Online Table A.6. Goodness of Fit - Multinational Acquisitions - Alternative Control Group /1

	Means Treated	Means Control (Pre)	Means Control (Post)	P-value (Pre)	P-value (Post)
Sales Growth Rate	0.05	-0.00	0.05	0.88	0.99
Lag Log Sales	16.76	14.62	16.75	0.17	1.00
Lag Log Value Added	15.61	13.59	15.61	0.19	1.00
Lag Log Employment	5.20	3.44	5.21	0.17	0.99
Lag Log Labor Costs	3.25	3.05	3.24	0.62	0.97
Lag Log Investment	11.84	7.78	11.81	0.34	0.99
Lag Log Fixed Assets	15.79	13.42	15.79	0.22	1.00
Lag Log RD Expenditure	6.91	2.03	6.53	0.46	0.95
Lag Log Exports	11.38	5.82	11.42	0.41	0.99
Lag Log Number of Export Markets	0.52	0.25	0.47	0.64	0.94
Lag Labor Share	0.41	0.49	0.42	0.74	0.95

Note: The table shows the goodness of fit of the one-to-five nearest neighbor matching algorithm when comparing firms acquired by a multinational (treated) to those acquired by another domestic firm (control). 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. All averages refer to the year before the treatment onset. 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.

Online Table A.7. Goodness of Fit - Multinational Acquisitions - Alternative Control Group /2

	Means Treated	Means Control (Pre)	Means Control (Post)	P-value (Pre)	P-value (Post)
Sales Growth Rate	0.05	0.03	0.04	0.96	0.98
Lag Log Sales	16.76	17.23	16.81	0.76	0.97
Lag Log Value Added	15.61	15.98	15.68	0.81	0.97
Lag Log Employment	5.20	5.19	5.24	1.00	0.97
Lag Log Labor Costs	3.25	3.51	3.27	0.53	0.96
Lag Log Investment	11.84	12.79	11.98	0.82	0.97
Lag Log Fixed Assets	15.79	16.21	15.83	0.83	0.98
Lag Log RD Expenditure	6.91	6.42	7.19	0.94	0.97
Lag Log Exports	11.38	14.41	12.65	0.65	0.85
Lag Log Number of Export Markets	0.52	0.64	0.55	0.83	0.95
Lag Labor Share	0.41	0.33	0.41	0.77	1.00

Note: The table shows the goodness of fit of the one-to-five nearest neighbor matching algorithm when comparing firms acquired by a multinational (treated) to those that are always owned by a multinational (control). 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. All averages refer to the year before the treatment onset. 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.

Online Table A.8. Goodness of Fit - Robot Adoption

	Means Treated	Means Control (Pre)	Means Control (Post)	P-value (Pre)	P-value (Post)
Sales Growth Rate	0.05	-0.01	0.03	0.81	0.94
Lag Log Sales	15.42	14.30	15.42	0.48	1.00
Lag Log Value Added	14.31	13.31	14.29	0.51	0.99
Lag Log Employment	4.02	3.25	4.00	0.53	0.99
Lag Log Labor Costs	3.15	3.00	3.15	0.70	0.99
Lag Log Investment	9.57	7.13	9.64	0.63	0.99
Lag Log Fixed Assets	14.50	12.95	14.48	0.40	0.99
Lag Log RD Expenditure	3.95	1.49	3.80	0.67	0.98
Lag Log Exports	8.25	4.94	8.22	0.64	1.00
Lag Log Number of Export Markets	0.35	0.22	0.36	0.77	0.99
Lag Labor Share	0.43	0.52	0.43	0.73	0.99

Note: The table shows the goodness of fit of the one-to-five nearest neighbor matching algorithm when comparing firms adopting robots (treated) to those that never adopt robots (control). 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. All averages refer to the year before the treatment onset. 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.

Online Table A.9. Why Do Multinational Acquisitions Boost Robot Adoption? /1

Dependent Variables:	Exp. via Foreign Parent$_{ft}$	Log(TFP)$_{ft}$	Log(Ext. R&D/Employees)$_{ft}$	Imp. of Foreign Tech.$_{ft}$
	(1)	(2)	(3)	(4)
MNE$_{ft}$	0.356***	0.210***	0.006	0.062
	(0.037)	(0.055)	(0.008)	(0.045)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Matched Sample	Yes	Yes	Yes	Yes
Observations	3,432	4,029	4,029	4,029

Note: The table shows the estimates of equation (1). Cohort-year-specific treatment effects are aggregated into a single (pooled) estimate using the size of each cohort as a weight. The unit of observation is a firm-year pair. In column (1), the dependent variable is a binary indicator equal to one if firm f exports via its multinational parental network in year t and zero if it uses an alternative channel (e.g., own means, specialized intermediaries, collective actions, or other means). This variable can only be defined for firms that export in a given year. In column (2), the dependent variable is the log of value added of firm f in year t. In column (3), the dependent variable is the log of the expenditure on external R&D per employee of firm f at time t. In column (4), the dependent variable is a binary indicator equal to one if firm f imports licenses and technical aid from abroad in year t and zero otherwise. MNE$_{ft}$ is a binary indicator equal to one if firm f is multinational-owned in year t and zero otherwise. Firms are matched using a one-to-five nearest neighbor matching algorithm based on the variables in Online Table A.4. Cluster standard errors at the firm level in parentheses. Significance levels: *** 0.01, ** 0.05, * 0.1.

Online Table A.10. Multinational Acquisitions, Sales, and Export Values

Dependent Variables:	Log(Sales)_{ft}	Log(Exports)_{ft}
	(1)	(2)
MNE_{ft}	0.205**	0.894*
	(0.087)	(0.540)
Firm FE	Yes	Yes
Year FE	Yes	Yes
Matched Sample	Yes	Yes
Observations	4,029	4,029

Note: The table shows the estimates of equation (1). Cohort-year-specific treatment effects are aggregated into a single (pooled) estimate using the size of each cohort as a weight. The unit of observation is a firm-year pair. In column (1), the dependent variable is the log of total sales of firm f in year t. In column (2), the dependent variable is the log of export values of firm f in year t. MNE_{ft} is a binary indicator equal to one if firm f is multinational-owned in year t and zero otherwise. Firms are matched using a one-to-five nearest neighbor matching algorithm based on the variables in Online Table A.4. Cluster standard errors at the firm level in parentheses. Significance levels: *** 0.01, ** 0.05, * 0.1.

Online Table A.11. Why Do Multinational Acquisitions Boost Robot Adoption? /2

Dependent Variable:	Robot Adoption$_{ft}$			
	(1)	(2)	(3)	(4)
Exp. via Foreign Parent$_{ft}$	0.143**	0.137**	0.137**	0.141**
	(0.062)	(0.061)	(0.061)	(0.061)
Log(TFP)$_{ft}$		0.032	0.032	0.033
		(0.026)	(0.026)	(0.026)
Log(Ext. R&D/Employees)$_{ft}$			-0.104	-0.105
			(0.085)	(0.086)
Imp. of Foreign Tech.$_{ft}$				-0.028
				(0.035)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Matched Sample	Yes	Yes	Yes	Yes
Observations	3,432	3,432	3,432	3,432

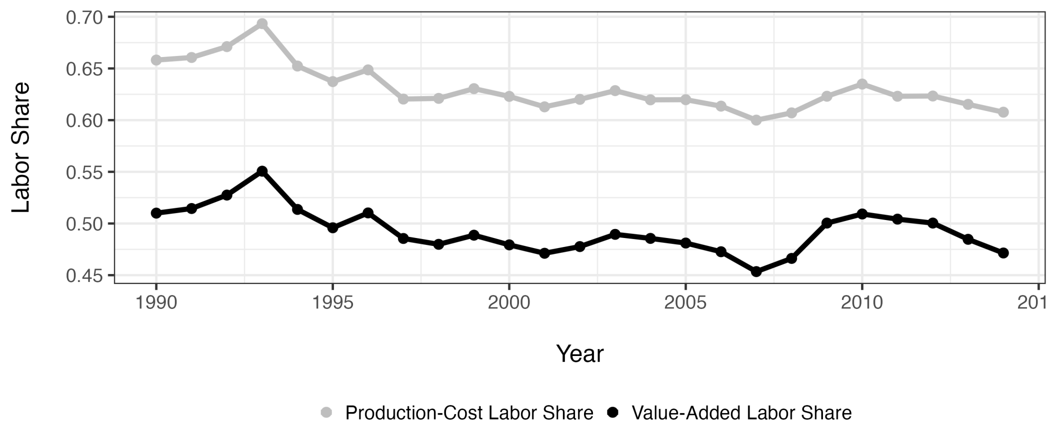
Note: The table shows the estimates obtained from a regression of a binary indicator equal to one since the first firm f adopts robots on firms' characteristics. The unit of observation is a firm-year pair. The dependent variable is a binary indicator equal to one since the first year firm f adopts a robot. Exp. via Foreign Parent$_{ft}$ is a binary indicator equal to one if firm f exports via its multinational parental network in year t and zero if it uses an alternative channel (e.g., own means, specialized intermediaries, collective actions, or other means). This variable can only be defined for firms that export in a given year. Log(Value Added)$_{ft}$ is the log of value added of firm f in year t. Log(Ext. R&D/Employees)$_{ft}$ is the log of the expenditure on external R&D per employee of firm f at time t. Imp. of Foreign Tech.$_{ft}$ is a binary indicator equal to one if firm f imports licenses and technical aid from abroad in year t and zero otherwise. Firms are matched using a one-to-five nearest neighbor matching algorithm based on the variables in Online Table A.4. Cluster standard errors at the firm level in parentheses. Significance levels: *** 0.01, ** 0.05, * 0.1.

Online Table A.12. Type of Manufacturing

Dependent Variables:	Batch Manuf.$_{ft}$	Mass Manuf.$_{ft}$	Mixed Manuf.$_{ft}$	Continuous Manuf.$_{ft}$
	(1)	(2)	(3)	(4)
MNE$_{ft}$	-0.066	-0.043	0.012	0.091***
	(0.074)	(0.075)	(0.026)	(0.028)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Matched Sample	Yes	Yes	Yes	Yes
Observations	3,985	3,985	3,985	3,985

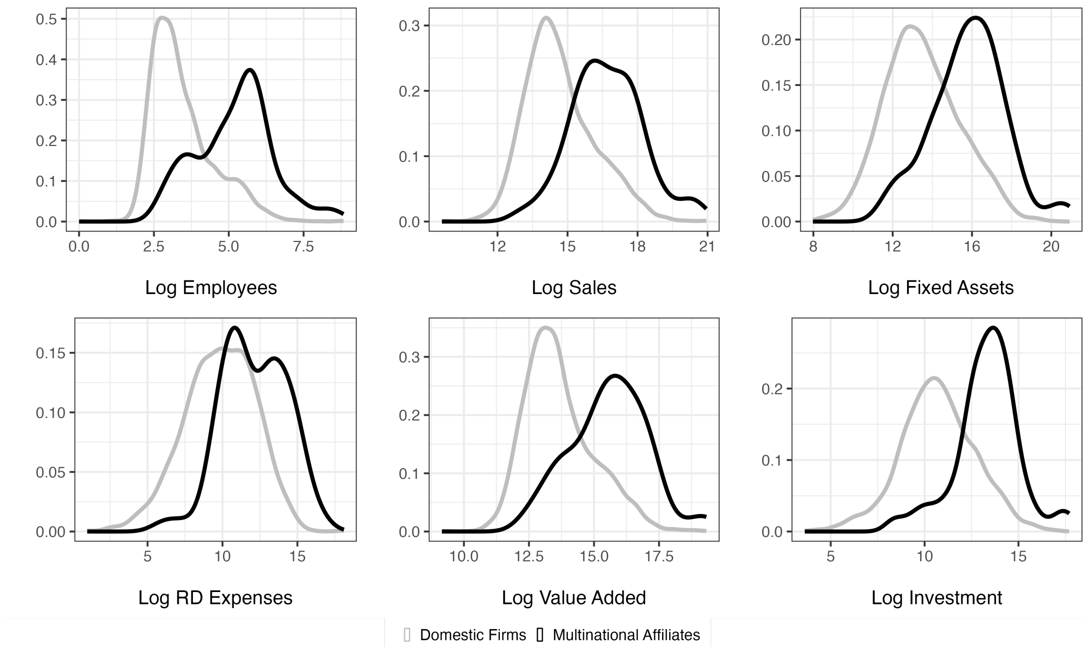
Note: The table shows the estimates of equation (1). Cohort-year-specific treatment effects are aggregated into a single (pooled) estimate using the size of each cohort as a weight. The unit of observation is a firm-year pair. In column (1), the dependent variable is a binary indicator equal to one if firm f performs batch manufacturing in year t and zero otherwise. In column (2), the dependent variable is a binary indicator equal to one if firm f performs mass manufacturing in year t and zero otherwise. In column (3), the dependent variable is a binary indicator equal to one if firm f performs mixed manufacturing in year t and zero otherwise. In column (4), the dependent variable is a binary indicator equal to one if firm f performs continuous manufacturing in year t and zero otherwise. These activities are mutually exclusive. MNE$_{ft}$ is a binary indicator equal to one if firm f is multinational-owned in year t and zero otherwise. Firms are matched using a one-to-five nearest neighbor matching algorithm based on the variables in Online Table A.4. Cluster standard errors at the firm level in parentheses. Significance levels: *** 0.01, ** 0.05, * 0.1.

Online Figure A.1. Labor Share: Value Added versus Production Costs



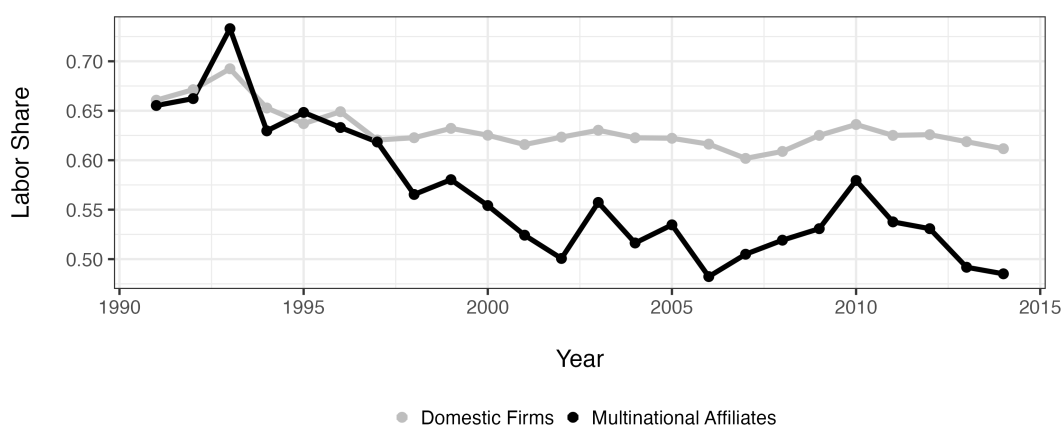
Note: The figure plots trends of the value-added and production-cost labor share over time. I define the value-added labor share as the ratio of labor compensation to gross value added. Labor compensation is calculated as the product of the average labor cost—which covers salaries and social security contributions—and the number of employees. Gross value added is computed as the difference between total sales and expenditure on intermediate inputs. Expenditure on intermediate inputs consists of labor compensation (as defined above), costs of physical inputs (including raw materials and energy), and payments for external services, and is adjusted for changes in inventories during that year. I define the production-cost labor share as the ratio of labor compensation to expenditure on intermediate inputs. Both labor compensation and expenditure on intermediate inputs are defined as above.

Online Figure A.2. Density Plots by Ownership



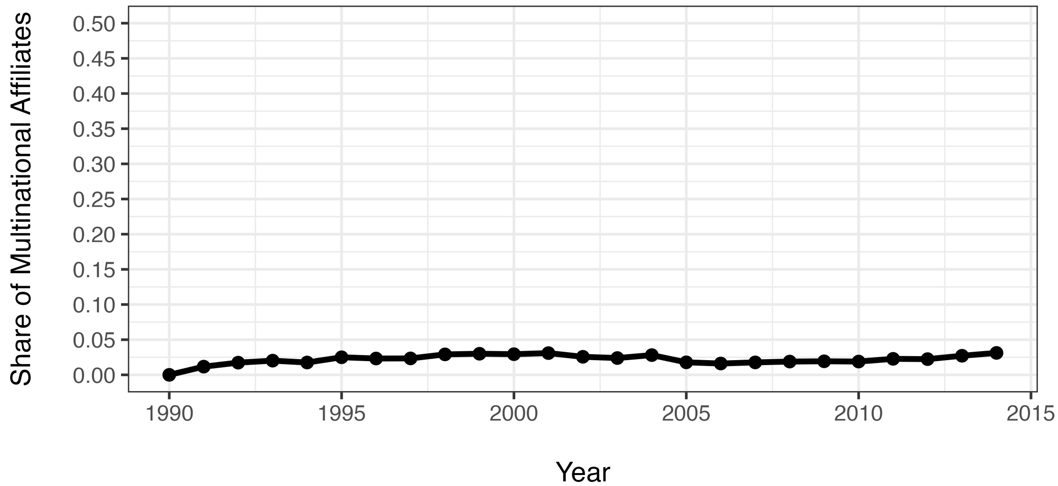
Note: The figure shows the empirical distribution of the log of the number of employees, sales, fixed assets, R&D expenses, value added, and investment by ownership type. I compute the distributions for domestic-owned firms based on their lifetime characteristics. I compute them only for the years before the acquisition date for multinational affiliates.

Online Figure A.3. Multinational Ownership and the Labor Share - Production Costs



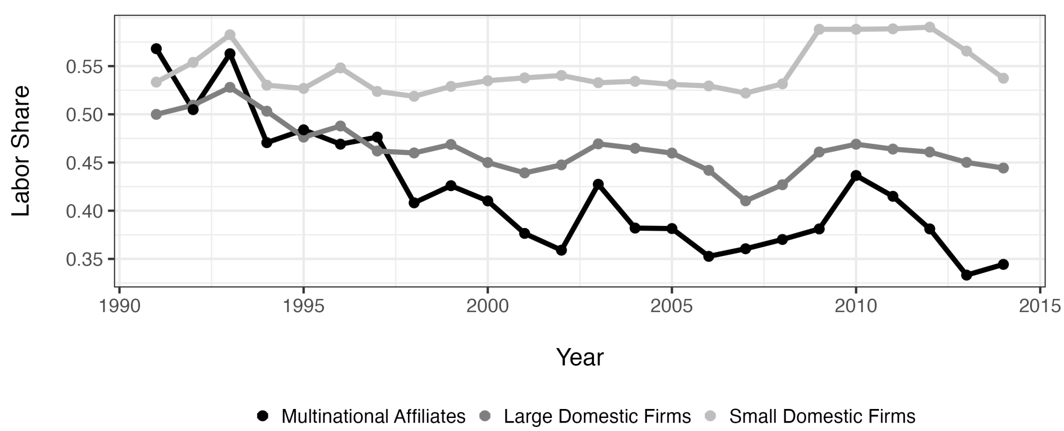
Note: The figure reproduces Figure 1 but using the production-cost labor share instead of the value-added labor share.

Online Figure A.4. Share of Multinational Affiliates over Time



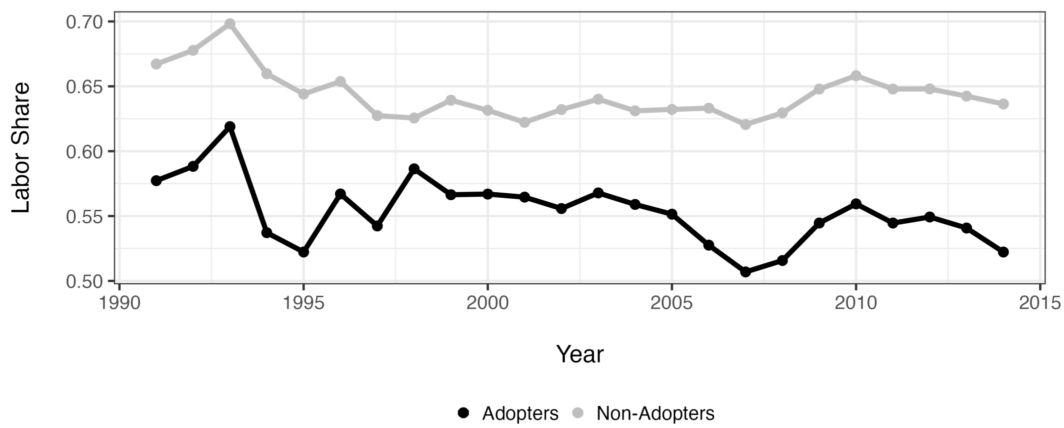
Note: The figure shows the proportion of firms owned by multinationals relative to the total number of firms in each sample year. Due to my sample selection criteria in Section 2.1, no firm is owned by a multinational in 1990.

Online Figure A.5. Multinational Ownership and the Labor Share - Conditional on Firm Size



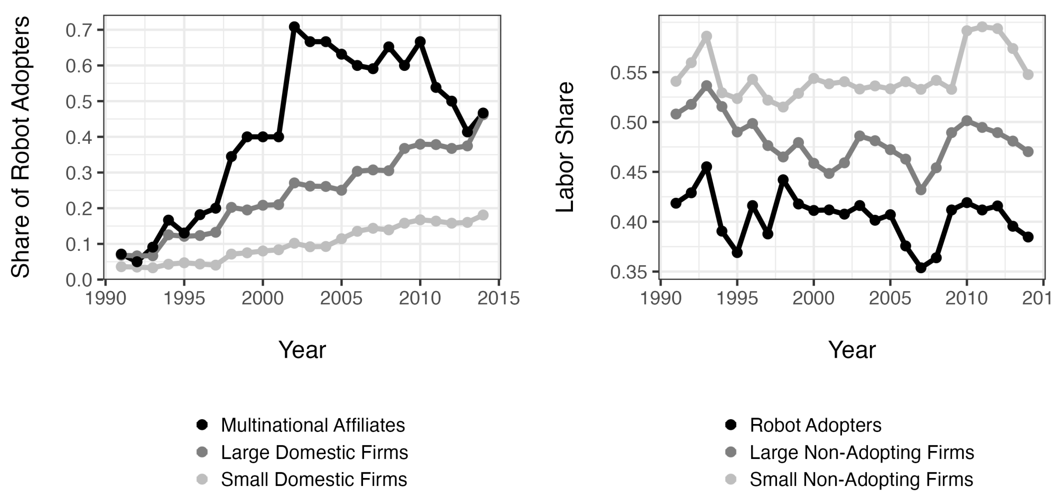
Note: The figure replicates Figure 1, but it separates domestic firms into two groups: those with employment levels above the sample median (Large Domestic Firms) and those with employment levels below the sample median (Small Domestic Firms).

Online Figure A.6. Robot Adoption and the Labor Share - Production Costs



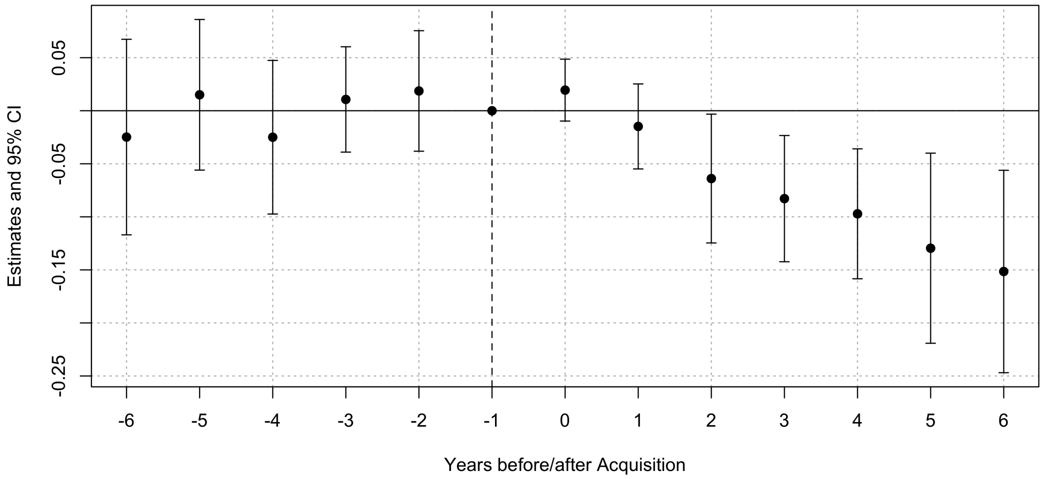
Note: The figure reproduces the right panel of Figure 2 but using the production-cost labor share instead of the value-added labor share.

Online Figure A.7. Multinational Ownership, Robot Adoption, and the Labor Share - Conditional on Firm Size



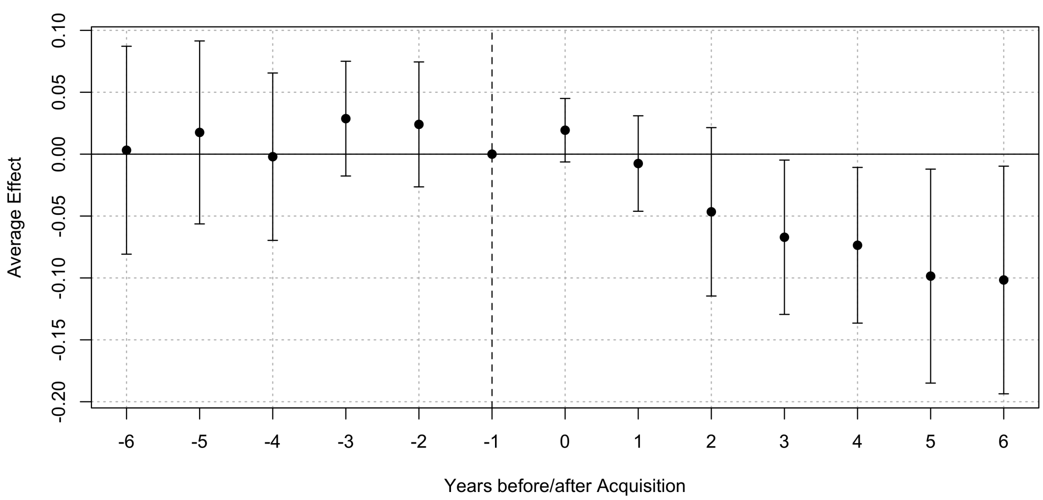
Note: The figure replicates Figure 2, but it separates domestic firms and non-adopting firms into two groups: those with employment levels above the sample median (Large Domestic Firms or Large Non-Adopting Firms) and those with employment levels below the sample median (Small Domestic Firms or Small Non-Adopting Firms).

Online Figure A.8. Multinational Acquisitions and Labor Share Dynamics - Industry Trends



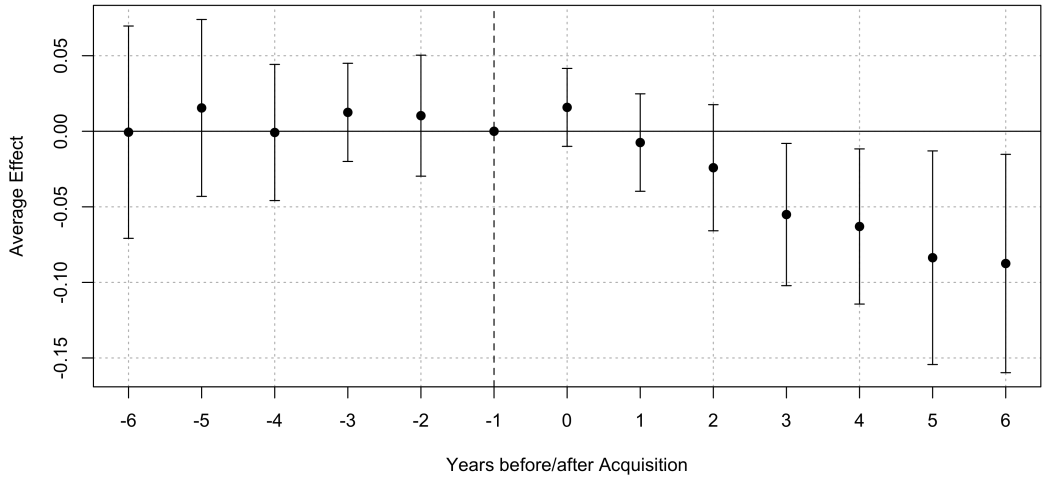
Note: The figure reproduces Figure 3 but replacing year fixed effects with industry-by-year fixed effects. The number of observations is the same as in the original figure.

Online Figure A.9. Multinational Acquisitions and Labor Share Dynamics - Alternative Matching



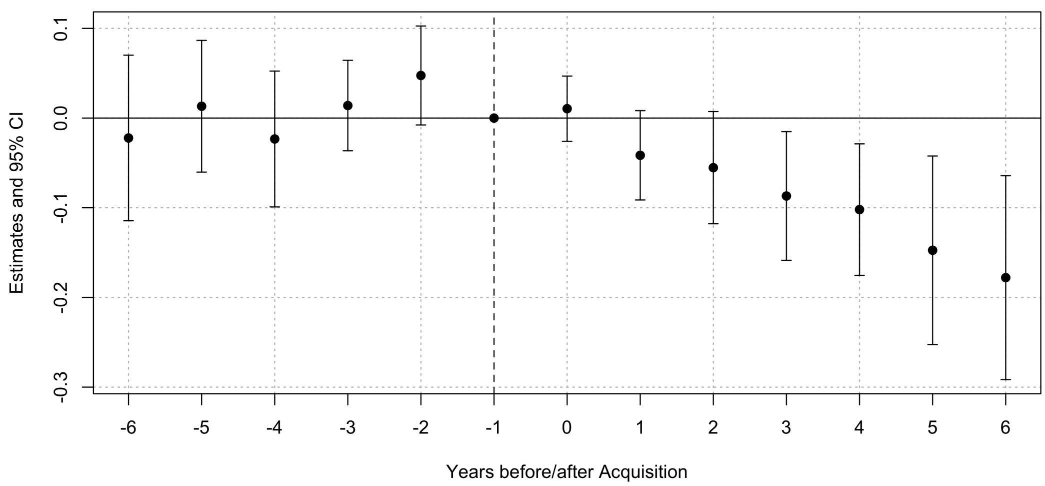
Note: The figure reproduces Figure 3 but using a one-to-three nearest neighbor algorithm. There are 3,111 observations.

Online Figure A.10. Multinational Acquisitions and Labor Share Dynamics - Production Costs



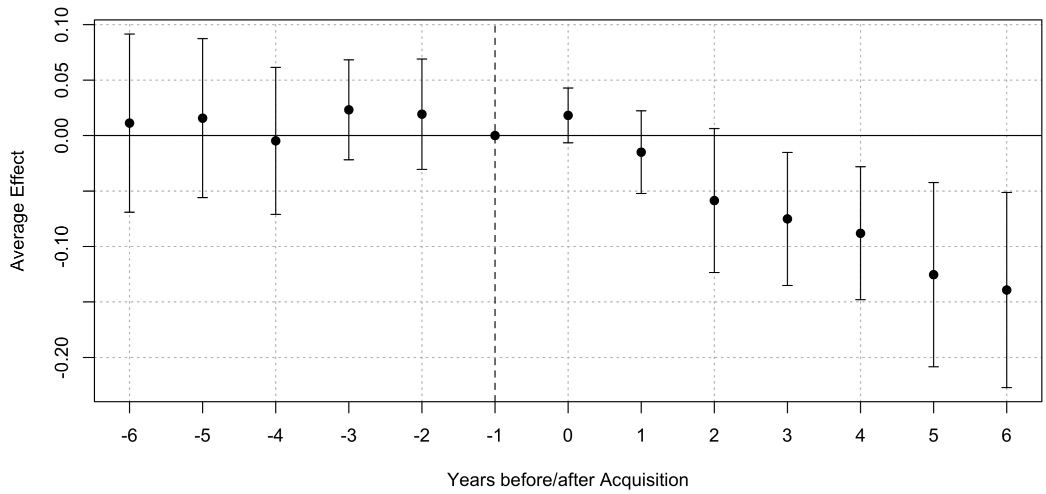
Note: The figure reproduces Figure 3 but using the production-cost labor share as the outcome variable. The number of observations is the same as in the original figure.

Online Figure A.11. Multinational Acquisitions and Labor Share Dynamics - Alternative Sample



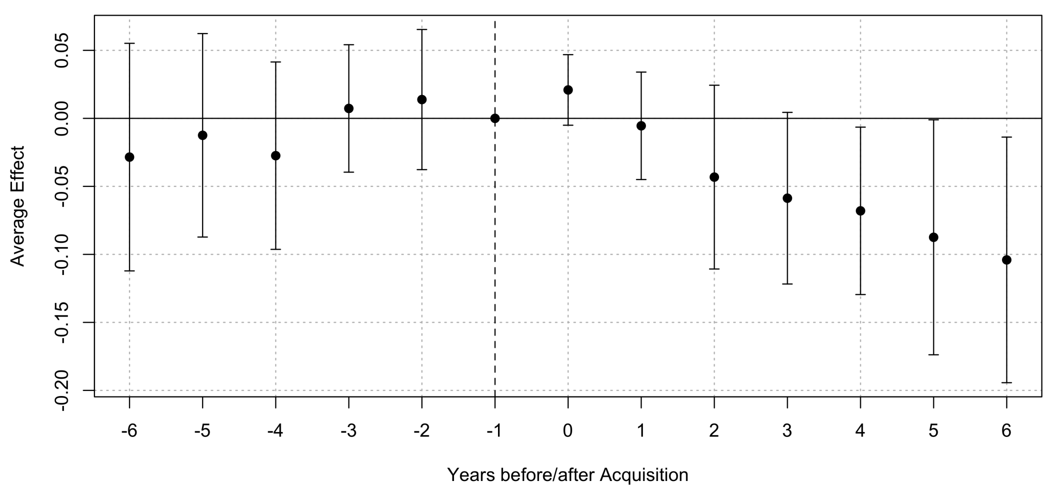
Note: The figure reproduces Figure 3 but excluding firms acquired in 1991 and 1992. There are 3,852 observations.

Online Figure A.12. Multinational Acquisitions and Labor Share Dynamics - Domestic Mergers



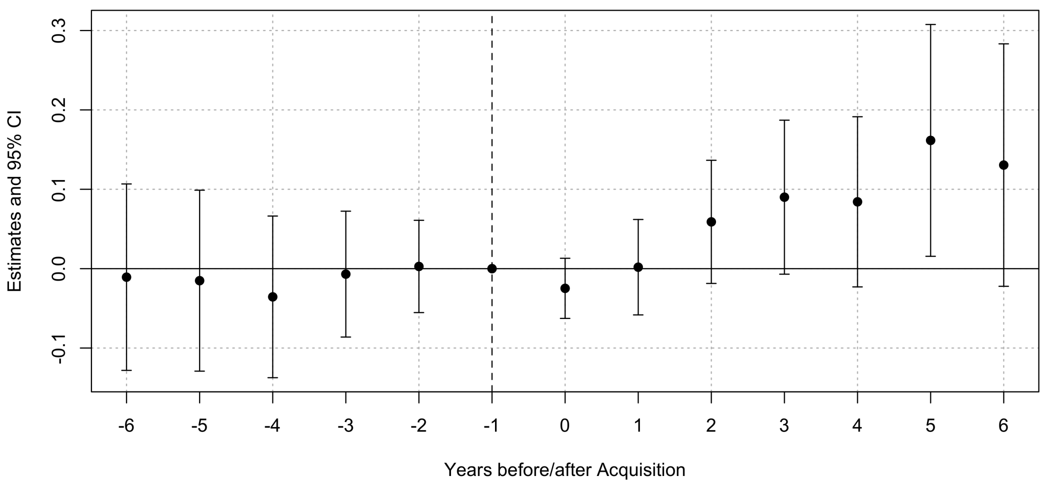
Note: The figure reproduces Figure 3 but using firms involved in domestic mergers as the control group. There are 4,060 observations.

Online Figure A.13. Multinational Acquisitions and Labor Share Dynamics - Greenfield FDI



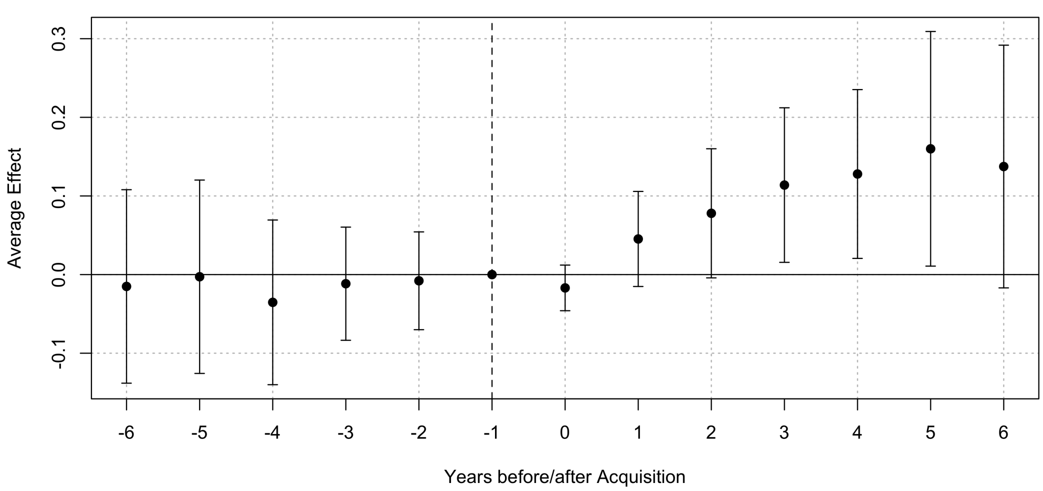
Note: The figure reproduces Figure 3 but using firms always owned by a multinational as the control group. There are 1,965 observations.

Online Figure A.14. Multinational Acquisitions and Robot Adoption Dynamics - Industry Trends



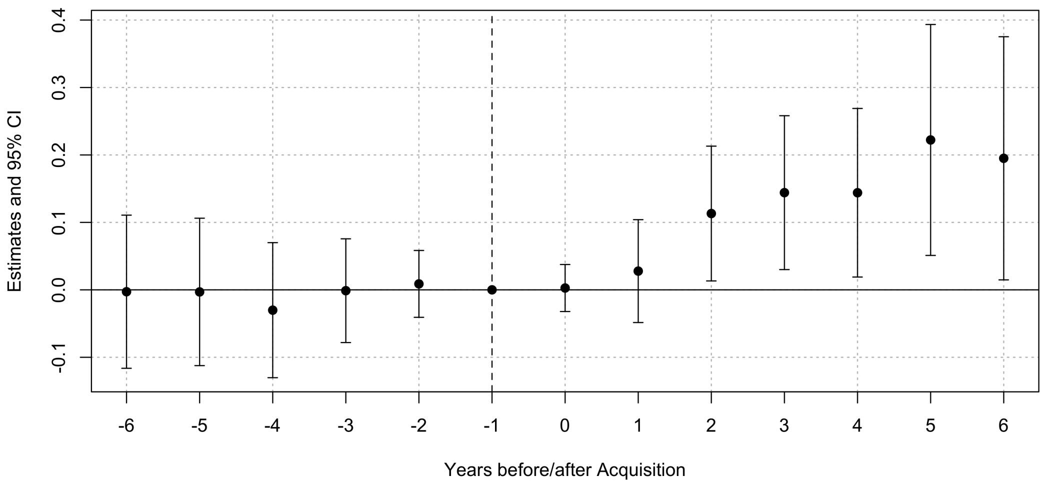
Note: The figure reproduces Figure 4 but replacing year fixed effects with industry-by-year fixed effects. The number of observations is the same as in the original figure.

Online Figure A.15. Multinational Acquisitions and Robot Adoption Dynamics - Alternative Matching



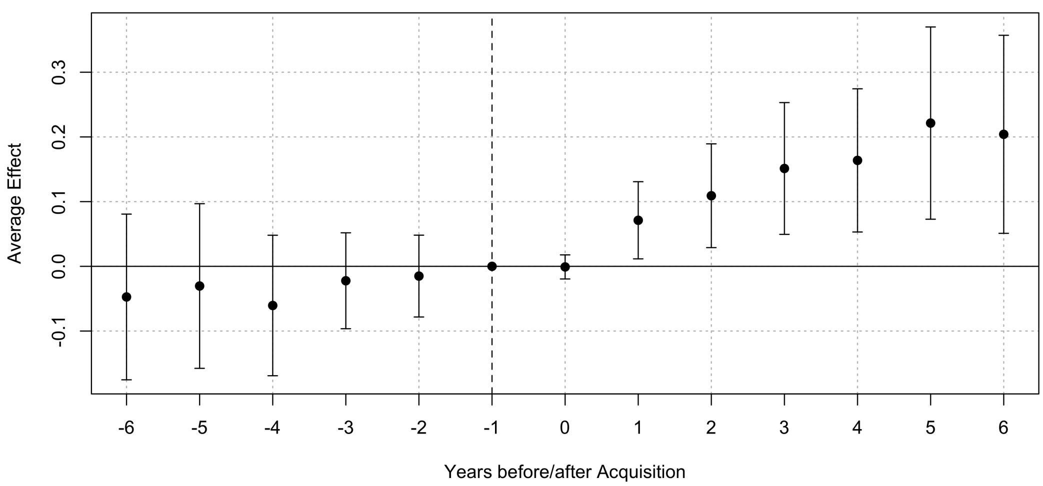
Note: The figure reproduces Figure 4 but using a one-to-three nearest neighbor algorithm. There are 3,111 observations.

Online Figure A.16. Multinational Acquisitions and Robot Adoption Dynamics - Alternative Sample



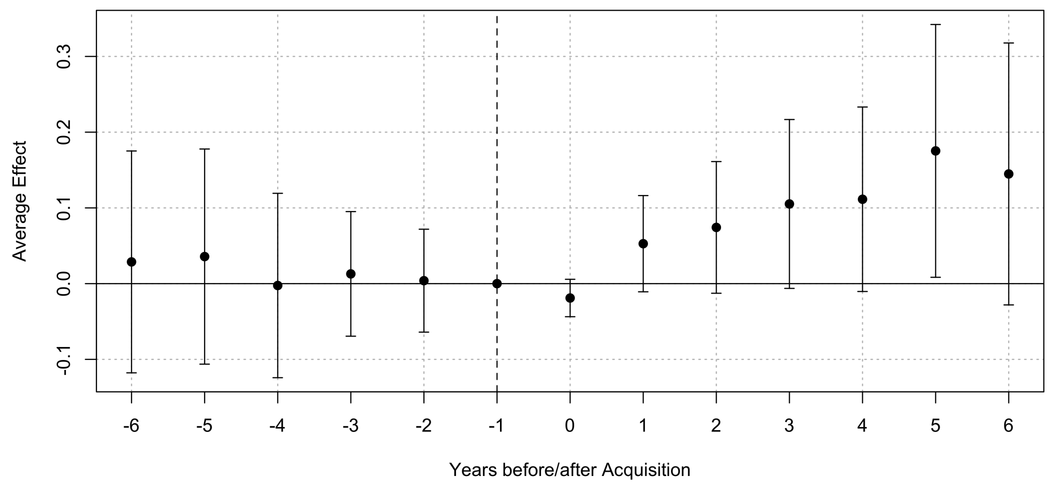
Note: The figure reproduces Figure 4 but excluding firms acquired in 1991 and 1992. There are 3,852 observations.

Online Figure A.17. Multinational Acquisitions and Robot Adoption Dynamics - Domestic Mergers



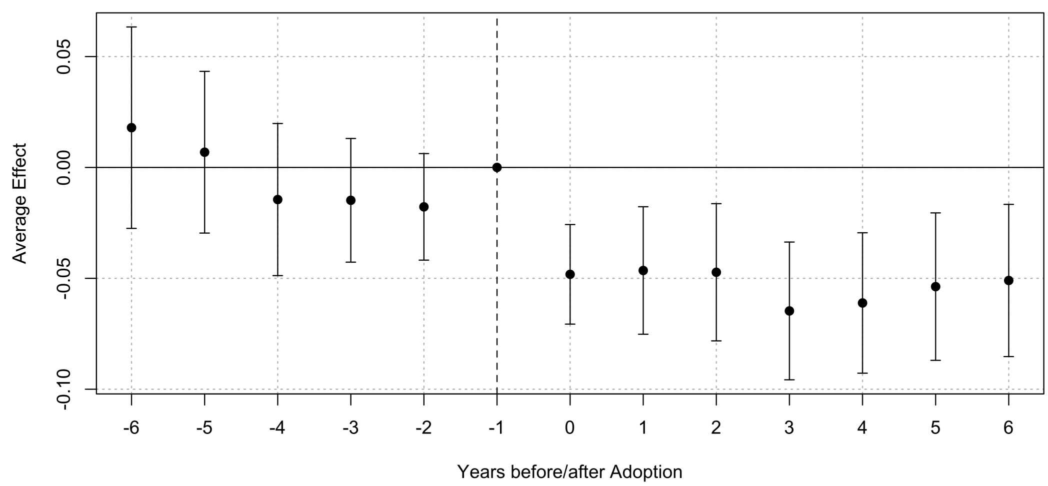
Note: The figure reproduces Figure 4 but using firms involved in domestic mergers as the control group. There are 4,060 observations.

Online Figure A.18. Multinational Acquisitions and Robot Adoption Dynamics - Greenfield FDI



Note: The figure reproduces Figure 4 but using firms always owned by a multinational as the control group. There are 1,965 observations.

Online Figure A.19. Robot Adoption and Labor Share Dynamics - Production Costs



Note: The figure reproduces Figure 5 but using the production-cost labor share as the outcome variable. The number of observations is the same as in the original figure.

A.2 Additional Details about the Firm-Level Data

The table below describes the main variables in the ESEE data.

Description of ESEE Variables

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

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

Despite its richness, the ESEE data also come with some limitations. First, firms do not disclose the identity of their multinational owners, which prevents distinguishing between vertical and horizontal FDI or assessing whether parents from countries where robots are highly diffused are more likely to encourage robot adoption. Second, the survey does not report if a firm is owned by a Spanish multinational. The data also contain missing values. I deal with them using a forward imputation criterion. If a binary indicator is missing, I impute its value with the first non-missing previous value. If a continuous variable is missing, I impute it with the average between two consecutive non-missing years. I only apply these criteria if the missing spell is less than three years.

A.3 Additional Details about the Aggregate Data

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

Merging data from AMNE, IFR, and WIOD SEA also requires tackling two challenges. First, one has to homogenize industry definitions. AMNE and WIOD follow the ISIC review 4 classification, whereas the IFR has its own system. However, since the IFR closely follows the ISIC review 4, it is possible 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 industries: "A" (Agriculture, forestry and fishing), "B" (Mining and quarrying), "C1012" (Manufacture of food products, beverages and tobacco products), "C1315" (Manufacture of textiles, wearing apparel, leather and related products), "C16" (Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials), "C1718" (Manufacture of paper and paper products, printing and reproduction of recorded media), "C19" (Manufacture of coke and refined petroleum products), "C2021" (Manufacture of chemicals chemical products, pharmaceuticals, medicinal chemical and botanical products), "C22" (Manufacture of rubber and plastics products), "C23" (Manufacture of other non-metallic mineral products), "C24" (Manufacture of basic metals), "C25" (Manufacture of fabricated metal products, except machinery and equipment), "C26" (Manufacture of computer, electronic and optical products), "C27" (Manufacture of electrical equipment), "C28" (Manufacture of machinery and equipment), "C29" (Manufacture of motor vehicles, trailers and semi-trailers), "C30" (Manufacture of other transport equipment), "DE" (Electricity, gas, steam and air conditioning supply), "F" (Construction), "P" (Education and R&D).

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

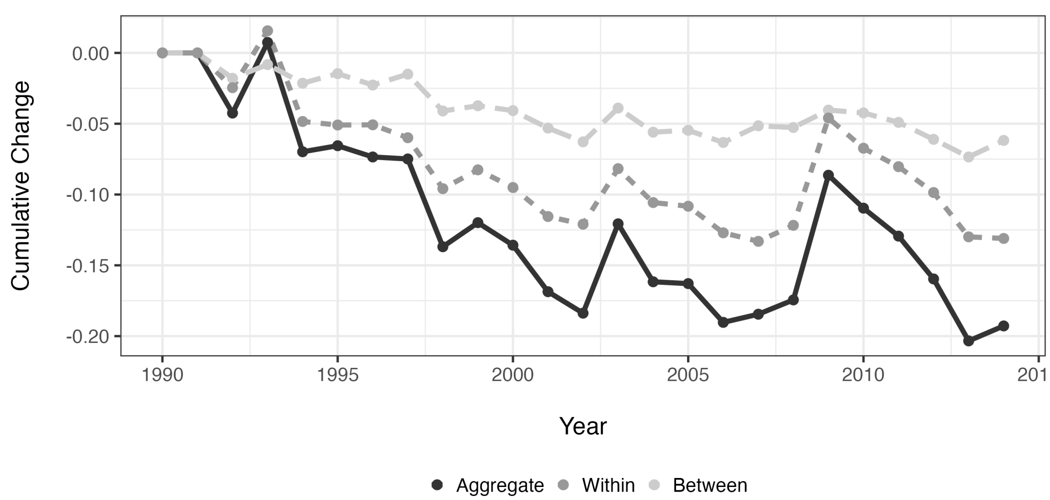
A.4 Decomposing the Labor Share

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

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

Changes in the value-added labor share can be attributed to the sum of changes in the unweighted mean of the value-added labor share ($\overline{ls}_t$), which reflects within-group dynamics, and changes in the covariance between the employment share of each group (s_{it}) and its value-added labor share (ls_{it}), which captures between-group reallocation. Online Figure A.20 shows that the within-group component accounts for 73% of the total value-added labor share reduction, indicating that changes among multinational affiliates are key drivers of manufacturing value-added labor share dynamics.

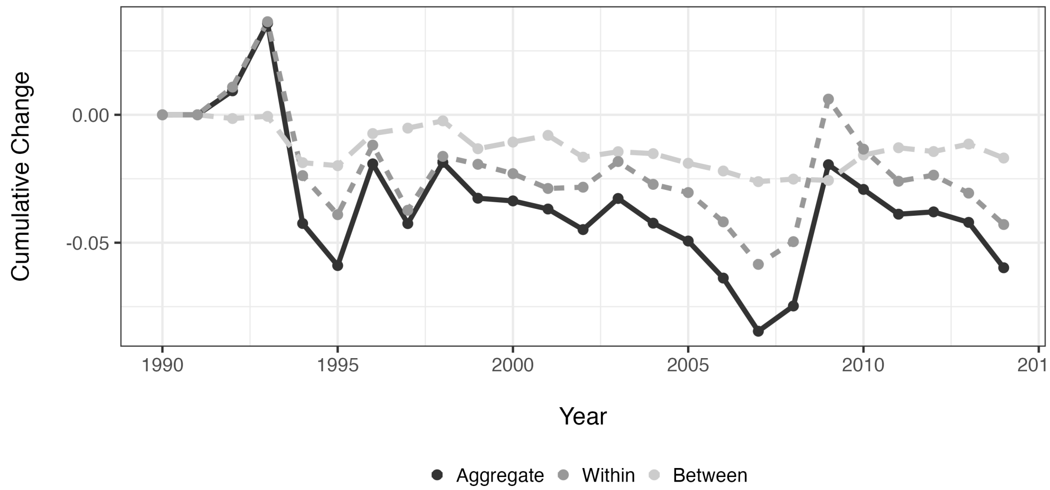
Online Figure A.20. LABOR SHARE DECOMPOSITION - OLLEY AND PAKES /1



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

I also apply the decomposition in equation (A.1) to the group of robot adopters and non-adopting firms. Online Figure A.21 shows that the within-group component accounts for 72% of the total value-added labor share reduction, suggesting that robot adoption is also a key driver of changes in the manufacturing value-added labor share.

Online Figure A.21. Labor Share Decomposition - Olley and Pakes /2



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

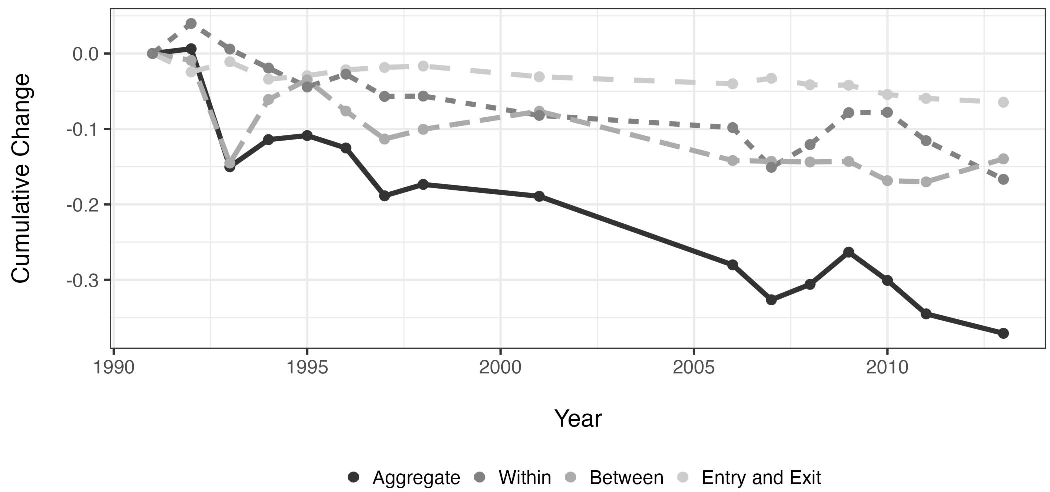
Melitz and Polanec Decomposition. Following Autor et al. (2020), I express the changes in the manufacturing value-added labor share between year $t-1$ and t as follows:[23]

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

The index St denotes firms that survive between $t-1$ and t. Et denotes firms that enter the sample in year t, while Xt denotes firms that exit the sample in year t. $s_{Gt} = \sum_{i \in G} s_{it}$ is the employment share of group G in year t. $ls_{Gt} = \sum_{i \in G}(s_{it}/s_{Gt}) ls_{it}$ is the group's average value-added labor share. Changes in the value-added labor share equal the sum of four elements: (1) changes in the unweighted value-added labor share mean of survivors, (2) employment share reallocation between survivors, (3) the value-added labor share of new entrants and exiting firms relative to survivors (see Melitz and Polanec, 2015, for a discussion). In Online Figure A.22, I apply equation (A.2) to the sub-sample of multinational affiliates. The reallocation of employment shares from firms with higher to those with lower value-added labor share explains about 52% of the total decline among multinational affiliates. The within-firm change is also negative, and explains about 31% of the total reduction. The contribution of entry and exit is roughly stable over time.

[23] Melitz and Polanec (2015) originally proposed this decomposition for total factor productivity.

Online Figure A.22. Labor Share Decomposition - Melitz Polanec



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

A.5 Preliminary Evidence using Aggregate Data

Using data from 37 middle- and high-income countries across 20 industries (see Section 2.2), I show that the facts in Figures 1 and 2 are not unique to the Spanish manufacturing industry. I estimate the following equation:

$$y_{ijt} = \beta X_{ijt} + \alpha_{ij} + \alpha_t + \varepsilon_{ijt}, \tag{A.3}$$

where i denotes countries, j industries, and t years. In this regression, y_{ijt} is the outcome variable, X_{ijt} is the explanatory variable, α_{ij} represents country-by-industry fixed effects, α_t denotes year fixed effects, and ε_{ijt} is the error term. To visualize the results, I apply the Frisch–Waugh–Lovell (FWL) theorem as follows:

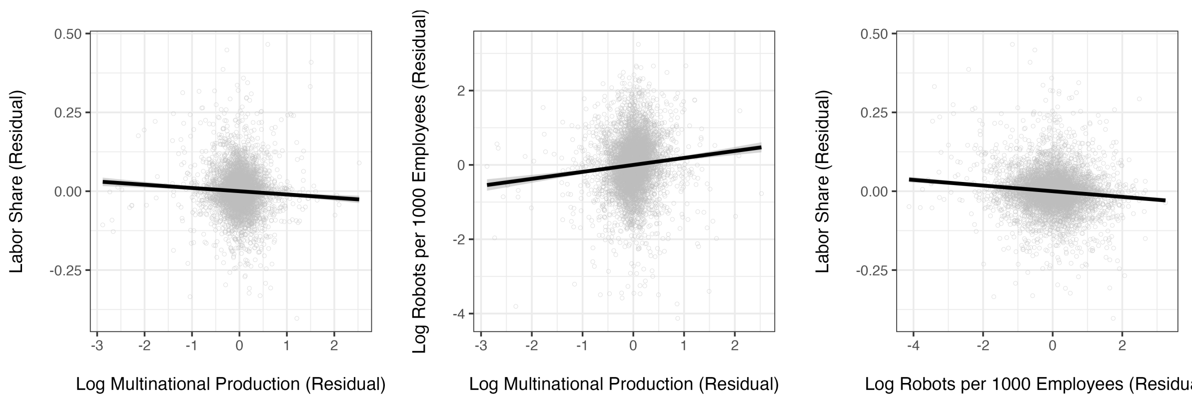
1. Regress y_{ijt} on the country-by-industry and year fixed effects and store the residuals.

2. Regress X_{ijt} on the country-by-industry and year fixed effects and store the residuals.

3. Regress the demeaned y_{ijt} on the demeaned X_{ijt}.

Online Figure A.23 displays a scatter plot of the demeaned variables and the corresponding linear fit. In the left panel, the dependent variable is the value-added labor share and the main regressor is the log of multinational production (i.e., total sales of foreign affiliates in industry j of country i in year t). In the middle panel, the dependent variable is the log of the number of industrial robots per thousand employees, a standard measure of robots' diffusion, and the main regressor is the log of multinational production. In the right panel, the dependent variable is the value-added labor share and the main regressor is the log of the number of industrial robots per thousand employees.

Online Figure A.23. Multinational Production, Robot Adoption, and the Labor Share



Note: The figure shows the estimates of equation (A.3). The left panel of the figure shows the correlation between the value-added labor share and the log of multinational production in industry j of country i in year t. The middle panel shows the correlation between the log of the number of industrial robots per thousand employees and the log of multinational production in industry j of country i in year t. The right panel of the figure shows the correlation between the value-added labor share and the log of the number of industrial robots per thousand employees in industry j of country i in year t. All variables are demeaned after projecting out country-by-industry and year fixed effects. In each panel, 95% confidence intervals around the fitted values are computed using heteroscedasticity-robust standard errors. All correlations are significant at the 5% level.

Online Table A.13 shows the estimate of β from equation (A.3) underlying each panel of Online Figure A.23. In terms of magnitude, after controlling for country-by-industry and time fixed effects, a 1% increase in the log of multinational production correlates with a reduction in the value-added labor share by 0.01 percentage points (1.75% relative to the sample average) and an increase in the stock of robots per thousand employees by 0.187%. In turn, a 1% increase in the stock of robots per thousand employees correlates with a reduction in the value-added labor share by 0.009 percentage points (1.57% relative to the sample average).

Online Table A.13. Multinationals, Robots, and the Labor Share

Dependent Variables:	Labor Share$_{ijt}$ (1)	Log(Robots per 1000 Employees)$_{ijt}$ (2)	Labor Share$_{ijt}$ (3)
Log(Multinational Production)$_{ijt}$	-0.010***	0.187***	
	(0.004)	(0.040)	
Log(Robots per 1000 Employees)$_{ijt}$			-0.009***
			(0.002)
Country-Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	6,514	6,514	6,514

Note: The table shows the estimates of equation (A.3). The unit of observation is a country-industry-year tuple. In columns (1) and (3), the dependent variable is the value-added labor share. In column (2), the dependent variable is the log of the number of industrial robots per thousand employees. Log(Multinational Production)$_{ijt}$ is the log of multinational production (i.e., total sales of foreign affiliates in industry j of country i in year t). Log(Robots per 1000 Employees)$_{ijt}$ is the log of the number of industrial robots per thousand employees. Heteroscedasticity robust standard errors in parentheses. Significance levels: *** 0.01, ** 0.05, * 0.1.

A.6 Implementation of the Counterfactuals

I consider the following equations:

$$LS_{ft} = \widehat{\beta}_1 \times MNE_{ft} + \alpha_f + \alpha_t + u_{ft}, \tag{A.4}$$

$$R_{ft} = \widehat{\beta}_2 \times MNE_{ft} + \delta_f + \delta_t + v_{ft}. \tag{A.5}$$

LS_{ft} is the labor share of firm f in year t. R_{ft} is an indicator equal to one since the first year firm f adopts robots. MNE_{ft} is an indicator equal to one if firm f is multinational-owned in year t. α_f, δ_f, α_t, and δ_t are firm and year-level fixed effects. I use $\widehat{\beta}_1$ and $\widehat{\beta}_2$ from column (1) of Table 1 and Table 2, respectively. Fixed effects are estimated from equations (A.4) and (A.5) using the estimator of Sun and Abraham (2021) on the full sample. I consider two counterfactual scenarios:

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

$$LS^{(1)}_{ft} = \widehat{\beta}_1 \times (1 - \widehat{\beta}_2) \times MNE_{ft} + (1 - \widehat{\beta}_2) \times \widehat{\alpha}^{(1)}_f + \widehat{\alpha}_t + \widehat{u}_{ft}. \tag{A.6}$$

Where:

$$\widehat{\alpha}^{(1)}_f = \widehat{\alpha}_f - (\mathbb{E}[\widehat{\alpha}_f | MNE_{ft} = 1] - \mathbb{E}[\widehat{\alpha}_f | MNE_{ft} = 0]) \times MNE_{ft}. \tag{A.7}$$

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

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

$$LS_{ft}^{(2)} = \widehat{\alpha}_f^{(1)} + \widehat{\alpha}_t + \widehat{u}_{ft}. \tag{A.8}$$

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

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

B Theoretical Appendix

B.1 A Model of Robot Adoption with Heterogeneous Firms

Environment. The economy consists of a large number of heterogeneous firms, each denoted by f, operating over an infinite horizon, with periods indexed by t. Within each period, the sequence of events unfolds as follows. First, firms may be acquired by a foreign multinational; once acquired, they remain under multinational ownership forever. Second, firms decide whether to adopt robots, a choice that, once made, is irreversible. Finally, firms produce and sell their output.

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

$$Y_{ft} = z_{ft} \left(\int_0^1 y_{ft}(i)^{\frac{\sigma-1}{\sigma}} di \right)^{\frac{\sigma}{\sigma-1}}, \quad y_{ft}(i) = \mathbf{1}\{i \leq \bar{\iota}_{ft}(R_{ft})\} \gamma_{ft}(i) M_{ft}(i) + L_{ft}(i). \tag{B.9}$$

z_{ft} denotes Hicks-neutral productivity, $y_{ft}(i)$ is the output of each task, and $\sigma > 1$ is the elasticity of substitution between tasks. R_{ft} is a binary indicator equal to one if firm f employs robots in year t. $M_{ft}(i)$ and $L_{ft}(i)$ are the quantity of material inputs and labor employed in each task, and $\gamma_{ft}(i)$ is their relative productivity level. Equation (B.9) states that inputs are perfect substitutes in any task $i \leq \bar{\iota}(R_{ft})$. However, only labor can perform tasks $i > \bar{\iota}_{ft}(R_{ft})$. I introduce the following standard assumption:

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

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

$$c_{ft}(R_{ft}) = \frac{1}{z_{ft}} \left(\alpha_{ft} r_t^{1-\sigma} + \beta_{ft} w_t^{1-\sigma} \right)^{\frac{1}{1-\sigma}}, \tag{B.10}$$

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

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

$$p_{ft} = \frac{\theta}{\theta - 1} c_{ft}. \tag{B.11}$$

Firm revenues can be expressed as:

$$\pi_{ft}(R_{ft}) = \Omega_t \psi_{ft} c_{ft}(R_{ft})^{1-\theta}, \tag{B.12}$$

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

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

$$V_{ft}(R_{ft}) = \sum_{s=t}^{\infty} \beta^{s-t} \mathbb{E}_s \left[\pi_{fs}(R_{ft}) \right] - FC_{ft}(R_{ft}) \tag{B.13}$$

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

$$V_{ft}(1) \geq V_{ft}(0). \tag{B.14}$$

Multinational Acquisitions. Let W_{mt} be the net present value of multinational parent m in year t. I assume that this value is weakly increasing with the value of each affiliate f. Firm f is acquired by m if and only if the net present value of multinational parent m in year t when owning f is greater than its net present value without f:

$$W_{mt}^{f} - K_{ft} \geq W_{mt}^{-f}. \tag{B.15}$$

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

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

Model Predictions. The model delivers the following testable predictions:

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

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

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

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

These predictions imply that identifying the impact of multinational acquisitions on the labor share through robot adoption requires addressing firm selection. Section 5 empirically tackles this challenge.