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Foreign ownership and robot adoption

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Abstract
This paper shows that multinational enterprises (MNEs) spur the adoption of industrial robots. First, I document a positive and robust correlation between multinational production and robot adoption using a new cross-country industry-level panel. Second, using detailed data about Spanish manufacturing, I combine a difference-in-differences approach with a propensity score reweighing estimator and provide evidence that firms switching from domestic to foreign ownership become about 10% more likely to employ robots. The ability of expanding into foreign markets via the parental network is the key driver of the adoption choice. An empirical model of firm investment reveals that MNEs generate significant industry-level productivity gains but decreases the labor share by boosting robot adoption. However, the first effect is one order of magnitude larger than the second. These results provide new evidence about the efficiency versus equity trade-off that policymakers face when attracting MNEs.

Keywords: foreign ownership, industrial robots, total factor productivity, factor-biased productivity, labor share
JEL: F23; O33

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1 Introduction

Multinational enterprises (MNEs) are crucial players in the world economy. They shape global production through Foreign Direct Investment (FDI), are responsible for about two-thirds of international trade flows (UNCTAD, 2013), and are important transnational employers. From the host countries' standpoint, MNEs are frequently praised for bringing superior technology (Harrison and Rodríguez-Clare, 2010). Indeed, they often employ more innovative production methods and more efficient management procedures than domestic companies (Bloom, Genakos, Sadun and Van Reenen, 2012). For this reason, foreign-owned firms tend to be bigger and more productive. Governments hope that this knowledge may also flow to domestic-owned firms directly or indirectly linked to a multinational. If this happens, the potential benefits of MNEs' local presence amplify in a substantial way (Javorcik, 2004; Keller, 2021).[1]

However, since technological change is typically factor-biased (Doraszelski and Jaumandreu, 2018), attracting foreign investment may deliver not only aggregate gains but also induce distributional outcomes. In this paper, I show that MNEs spur the adoption of industrial robots.[2] This finding is new in the literature, and it raises potential distributional concerns: unlike standard capital-intensive technology, robots may increase productivity but replace workers in routine production tasks, and therefore pose an efficiency versus equity trade-off for policymakers.[3]

I exploit two data sources. The first is a new cross-country industry-level dataset containing the number of deployed robots and gross output produced by foreign-owned firms (which I call "multinational production") for 37 countries and 20 industries from 2005 to 2014. Using these data, I document that a one per cent multinational production increase correlates with 0.5% more robots per thousand employees, which is a standard measure of robots' diffusion (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020). The correlation is significant and robust to the inclusion of observed time-varying country-industry characteristics (e.g., capital-to-labor employment and wage ratio) and any time-varying country and industry-level shocks. I also show that this result is not driven by the top five robot markets (i.e., China, Germany, Japan, South Korea, and the US) or the automotive industry, which accounts alone for over

[1]These spillovers provide a potential rational for policy intervention. Typical policies to attract foreign investors include the creation of Investment Promotion Agencies (IPAs), Special Economic Zones, and tax breaks or subsidies (UNCTAD, 2018).

[2]Industrial robots 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). See International Federation of Robotics (2019).

[3]The difference between robots and standard capital inputs has been theoretically and empirically emphasized in a number of papers (Acemoglu and Restrepo, 2018b; Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020; Koch, Manuylov and Smolka, 2021).

80% of the worldwide robot stock in any sample year.

Multiple explanations may underlie the cross-country evidence. On the one hand, the results are consistent with multinational production increasing robot adoption. On the other, reverse causality and omitted factors preclude a causal interpretation. To make further progress in understanding whether foreign ownership boosts robot adoption, I use the firm-level ESEE survey data provided by the SEPI Foundation in Madrid. The data, which cover from 1990 to 2017, are a detailed and representative panel of the population of Spanish manufacturing firms and, crucially for this paper, report the share of firms' equity owned by foreign companies (i.e., headquartered outside of Spain) and a binary variable for whether or not a firm employs robots in a given year. I restrict the sample to two groups of firms. The first group includes firms that stay under domestic ownership throughout their life span. The second group contains firms that switch at most once from domestic to foreign ownership. Although firms belonging to the second group are only about 3% of the total, they account for a disproportionately large share of production and employment, are more innovative, and engage more in international trade than domestic-owned ones.[4]

The data reveal that even if robot adoption rates have steadily grown over time, the (unconditional) share of robot adopters among foreign-owned firms is twice as large than among domestic-owned ones in any year. This pattern holds across different manufacturing sectors and, although lower in magnitude, also after controlling for firm size (e.g., total sales). Next, I introduce an event-study specification to study how the probability of employing robots changes after switching from domestic to foreign ownership. When performing this exercise, I restrict my attention to ever acquired firms.[5] The identifying assumption is that not-yet-acquired firms are a credible counterfactual for acquired ones after controlling for firm-level time invariant heterogeneity, industry-level time-varying common shocks to all firms, and firm-level time-varying observed differences in levels (e.g., sales) and performance (e.g., sales growth rate). This specification reveals that, as of the first year after the acquisition, new affiliates are about 35% more likely to employ robots than in the year before the event. I find no evidence of anticipation effects.[6]

[4]Guadalupe, Kuzmina and Thomas (2012) and Koch and Smolka (2019) also document this pattern using the ESEE data. The fact that (future) foreign-owned firms are a positively selected sub-sample is also documented beyond the Spanish context (Setzler and Tintelnot, 2021; Alfaro-Ureña, Manelici and Vasquez, forthcoming).

[5]In a robustness, I obtain a similar pattern when including never acquired firms in the control group.

[6]Recent literature has shown that estimating event studies with a two-way fixed effects estimator fail to recover the treatment effect when treatment roll-out is staggered and the treatment effects change over time (Sun and Abraham, 2021; Borusyak, Jaravel and Spiess, 2021; Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021). To deal with this concern, I also estimate the event study using the method proposed by Sun and Abraham (2021). The results are qualitatively similar to the baseline

Although suggestive of a causal relationship, one may worry that the estimates are confounded by unobserved time-varying firm-level shocks that simultaneously influence the foreign acquisition decision and robot adoption (Blundell and Costa Dias, 2009). Absent firm-level experimental variation in equity share composition, I follow the approach of Guadalupe et al. (2012) and combine a difference-in-differences approach with an inverse probability reweighing (IPRW) estimator to address this concern.

The estimator works in two steps. First, for each firm in the sample, I estimate the probability of becoming foreign-owned as a function of an extensive set of controls in levels and growth rates. Second, I assign a weight of $1/\widehat{p}$ to acquired firms and $1/(1-\widehat{p})$ to always domestic ones, being $\widehat{p}$ the estimated first-stage probability. This reweighing scheme aims at making the two groups of firms comparable on observables before the acquisition. Then, I project a binary variable for whether a firm employs a robot in a given year on a binary variable for whether it is foreign-owned in that year and firm and industry-year fixed effects. The identifying assumption is that, post-reweighing and conditional on the included fixed effects, treatment is random. Using this procedure, I find that, after the acquisition, firms are on average 10% more likely to employ robots than comparable domestic producers, on average.[7] I use this estimate as my baseline and call it the "foreign ownership robot adoption premium". I also provide evidence that the premium is larger in industries characterized by lower adoption rates at the beginning of the sample period.

Various mechanisms may explain why being acquired by a foreign multinational spurs robot adoption. For instance, using the same data, previous literature has shown that the possibility of expanding into foreign markets via the parental network is a central driver of process and product innovation (Guadalupe et al., 2012) and skill-upgrading (Koch and Smolka, 2019). To the extent that robots are complementary to these activities, the increased foreign market access channel is also relevant in my context. An alternative hypothesis is that foreign acquisitions alleviate credit constraints, thus allowing firms to move closer to their first-best investment level (Harrison and McMillan, 2003; Manova, Wei and Zhang, 2015). Another possible explanation is that foreign parents directly transfer robot adoption knowledge to their affiliates. Indeed, previous literature has found extensive evidence of technology flows within multinational networks (Branstetter, Fisman and Foley, 2006; Keller and Yeaple, 2013; Bilir and Morales, 2020).

The richness of the ESEE survey allows me to test the explanatory power of these alternative mechanisms. To evaluate the foreign market access channel, I use a ques-

specification.

[7] By contrast, I find no evidence that acquired firms become more likely to use other automation-type non-robotic technologies (e.g., numerically controlled machines) that are older and less productivity-enhancing than robots (Acemoglu and Restrepo, 2020; Koch et al., 2021).

tion in the survey that asks firms whether they access export markets (if at all) via their foreign parental network or via other means. To assess the importance of credit constraints, I use information on firm expenditure on external R&D, an activity heavily dependent on firms' borrowing possibilities (Brown, Martinsson and Petersen, 2012). Finally, although the ESEE does not contain information about intra-firm activities, I proxy technology transfers with expenses on licenses and technical aid from abroad, possibly from the parent firm.

Using the same approach as in the baseline, I find that switching to foreign ownership boosts affiliates' foreign market access which, in turn, is a driver of robot adoption. Intuitively, acquired firms need to scale-up production to translate higher potential demand into actual sales, and robot adoption is one way to achieve this result. The estimates also reveal that the effect is stronger for newly acquired firms that did not export before the acquisition year. By contrast, I find no support for the other two hypotheses.

One interesting question is whether different types of acquisitions, e.g., from a domestic firm, produce different robot adoption outcomes. Providing an answer is relevant from a policy perspective because it reveals whether attracting foreign investment may deliver different outcomes than policies promoting, for instance, domestic mergers.[8] To do so, I exploit a survey question that asks firms if they are acquired by another domestic company. Using a similar strategy as in the baseline analysis, I provide evidence that firms acquired by a Spanish (non-multinational) company do not become more likely to employ robots. In the light of the previous discussion, one potential reason is that, by construction, companies only active in Spain do not offer a global network of contacts that their affiliates can leverage to expand in foreign markets and, therefore, do not provide sufficient incentives to increase production.

Since robot adoption allows to scale-up production and expand in global markets, one expects to find large within-firm gains associated with ownership switching. Indeed, I find that acquired firms increase sales and employment by about 37% and 22% respectively. However, switching to foreign ownership also redistributes income away from labor. Although wages increase by about 9%, the labor share in revenues falls post-acquisition, suggesting that firms tilt production towards capital-intensive activities.[9]

These insights allow me to parametrize a dynamic partial equilibrium firm invest-

[8]Another question is whether firms acquired by a multinational headquartered in Spain are also more likely to employ robots. In principle, given the documented importance of increased market access through the parental network, I expect that being acquired by a Spanish multinational produces similar outcomes as being acquired by a foreign one. Unfortunately, the ESEE survey does not report if a firm is acquired by a Spanish multinational, which makes it unfeasible to evaluate this hypothesis.

[9]This result is consistent with Koch and Smolka (2019) and Sun (2020).

ment model based on Doraszelski and Jaumandreu (2018), which I use to further analyze the gains and distributional implications of foreign ownership and robot adoption. In the model, firms combine physical inputs and labor with constant elasticity of substitution and make robot adoption choices to maximize profits. Firms' production function features labor-augmenting and total factor productivity (TFP), and I let both depend on past ownership structure and robot adoption choices. The main estimands of interest are the impact of foreign ownership and robot adoption on total factor and labor-augmenting productivity, which governs the physical inputs-to-labor ratio at the firm level. As standard in the literature (Doraszelski and Jaumandreu, 2013, 2018), I assume that productivity follows a first-order Markov process and, therefore, past ownership structure and robot adoption choices are mean independent of current idiosyncratic productivity shocks.

The results reveal the ratio of physical inputs to labor is about 40% larger in robot adopters than among non-adopting firms. After controlling for robot adoption, being foreign-owned does not directly alter firms' optimal input mix. Hence, the model estimates suggest that it is robot adoption, rather than foreign ownership per se, to be the main driver of increased within-firm inequality post-acquisition. By contrast, robot adoption and foreign ownership are associated with 29%, respectively 43%, higher TFP. I use these results to simulate two counterfactual scenarios. First, I simulate an economy without multinationals. When doing so, I account for the reduced-form effect that foreign ownership induces on robot adoption. Second, I consider a scenario without multinationals and robots. In each case, I start from the observed productivity distribution and simulate forward firm-specific total factor and labor-augmenting productivity paths using the estimated law of motions and shutting down one channel at a time.[10]

As a benchmark, the model-implied TFP and labour share total growth rates over the sample period are 0.60% and -18.07%, respectively. These figures are qualitatively similar to Doraszelski and Jaumandreu (2018). The counterfactual exercises suggest that an economy without multinationals and robots would have experienced negative total TFP growth (-0.50%) but a higher labour share (1.22%). Shutting down only multinational activity explains about 77% of the total TFP drop but only about 7% of the total labour share increase between scenarios. In each case, robots account for the remaining gap. Overall, the counterfactual exercises deliver two main insights. First, multinational activity produces significant TFP gains but puts downward pressure on the labor share by boosting robot adoption. However, the first effect is one order of

[10]To avoid dealing with sample selection, I perform the counterfactuals using the sub-sample of firms always active during the sample period. While the share of foreign-owned firms is about the same as in the original sample, the share of robot adopters is about twice as large. Hence, the results should be understood as an upper bound of the effects in the complete sample.

magnitude larger than the second. Although the model is silent about total welfare, this result offers new evidence about the efficiency versus equity trade-off that policymakers face when attracting foreign investment. Second, the model results also provide a new rationale for the observed decline in the manufacturing labor share across many countries. Grossman and Oberfield (forthcoming) include globalization and automation among the leading forces behind this phenomenon. My results reinforce and extend their argument. Rather than being different explanations, MNEs' activities (globalization) and robot adoption (technological change) jointly contribute to the observed decline. However, robots play a predominant role.

I organize the rest of the paper as follows. Section 2 connects this paper with previous literature. Section 3 introduces the data. Section 4 analyzes the correlation between MNEs' activities and robot adoption using cross-country industry-level data. Section 5 presents the baseline estimates of the foreign ownership robot adoption premium. Section 6 contains the model and the counterfactual simulations. Finally, Section 7 concludes.

2 Related Literature

This paper contributes to three strands of the literature. First, it provides new evidence about the technological impact of MNEs on the domestic economy. Second, it participates to the debate about the interplay of globalization and technological change. Finally, it adds to recent research about the effects of automation.

The first strand of the literature shows that multinationals boost host country productivity by promoting investment and technology upgrading (Aitken and Harrison, 1999; Javorcik, 2004; Blalock and Gertler, 2008; Harrison and Rodríguez-Clare, 2010; Guadalupe et al., 2012; Bloom et al., 2012; Bircan, 2019; Méndez-Chacón and Van Patten, 2021). However, the literature also acknowledges that this process is often skill-biased or factor-specific (Feenstra and Hanson, 1997; Koch and Smolka, 2019; Sun, 2020; Setzler and Tintelnot, 2021; Alfaro-Ureña, Manelici and Vasquez, 2021).

My contribution to this literature is twofold. First, I show that MNEs spur the adoption of industrial robots. Far from being standard capital-augmenting technology, they are labor-replacing technology and produce substantial societal impact, spanning labor markets (Graetz and Michaels, 2018; Acemoglu, Lelarge and Restrepo, 2020; Acemoglu and Restrepo, 2020; Humlum, 2021), international trade (Artuc, Paulo and Rijkers, 2018; Stapleton and Webb, 2020), public finance (Freeman, 2015), and electoral outcomes (Anelli, Colantone and Stanig, 2019).

Second, industrial robots are a directly measurable technology. Rather than inferring the technological content of FDI by comparing pre and post-acquisition firms' activities (e.g., changes in sales, R&D expenditures, or workforce composition), the ESEE data offer a direct measure of robotic technology adoption.

Showing that MNEs spur robot adoption is also informative about how globalization and technological change jointly shape the economy. On the one hand, globalization and technological change can lift millions of people out of poverty (Harrison, 2007). On the other, these two phenomena can fundamentally change societies. Moreover, as long as the benefits of globalization and technological change accrue to large, already more productive firms, the economic integration gains are hampered (Brynjolfsson and McAfee, 2014; Baldwin, 2019; Korinek and Stiglitz, 2021). This process can lead indeed to market power concentration, lower innovation rates and higher inequality (Autor, Dorn, Katz, Patterson and Van Reenen, 2020; De Loecker, Eeckhout and Unger, 2020). Quantifying the role of multinational enterprises in this process is key to designing informed policies towards foreign investment.

Finally, this paper contributes to the literature on automation, in particular robot adoption. First, I show how to identify and estimate the impact of robot adoption (and foreign ownership) on factor-biased and Hicks-neutral firm-level productivity. By doing so, I contribute to the literature about factor-bias technological change estimation (Doraszelski and Jaumandreu, 2013, 2018; Raval, 2019; Oberfield and Raval, 2021). Second, by showing that robot adoption boosts productivity but decreases the labor share, I add to the debate about the effects of automation at the firm-level (Acemoglu et al., 2020; Aghion, Antonin, Bunel and Jaravel, 2020; Koch et al., 2021; Humlum, 2021) and industry-level (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020; Hémous and Olsen, 2022).

3 Data

I use two different data sources. The first is a new cross-country industry-level dataset that I use to describe the aggregate correlation between robot adoption and multinational production. The second is a detailed firm-level panel that I exploit to study how switching from domestic to foreign ownership changes firms' propensity to employ robots.

3.1 Industry-Level Data

I create a new cross-country industry-level dataset with information about MNEs' activities and industrial robots. Data about multinational activity come from the Analytical Multinational Enterprises Database (AMNE) of the Organization for Economic Cooperation and Development (OECD). For each country-industry-year tuple, the AMNE database contains a breakdown of gross output by domestic and foreign producers (i.e., MNEs) from 2005 to 2016.[11]

Data about industrial robots come from the International Federation of Robotics (IFR). The IFR aggregates cross-country firm-level information at the industry level to match the ISIC review 4 classification. The IFR data contain the number of deployed industrial robots at the country-industry-year level. These data are the most widely used source for robot adoption studies and are praised for their reliability (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020).

I complement the first two sources with standard industry accounts (e.g., total production, employment, wages, investment, fixed assets, exchange rate, and price deflators) from the Socio-Economic Account (SEA) database of the World Input-Output Database (WIOD). The final dataset contains information about 37 countries and 20 industries from 2005 to 2014. Industries include agriculture, mining, 15 two-digit manufacturing sectors, electricity and water supply, and construction. I express all nominal variables in USD million at constant prices. I provide more details about the sample creation and data cleaning in Appendix B.1. Table B.1 shows sample summary statistics.

3.2 Firm-Level Data

The ESEE Survey. Firm-level data come from the *Encuesta sobre Estrategias Empresariales* (ESEE, or Survey on Business Strategies) administered by the SEPI Foundation in Madrid.[12] The survey, spanning from 1990 to 2017, is a joint effort of the Ministry of Industry and the SEPI Foundation, and it is designed to be representative of the population of manufacturing firms with ten or more employees located in Spain. In 1990, the SEPI Foundation interviewed 2,188 firms divided into two categories. The first group contains firms with more than 200 employees. The second group is composed of a stratified sample of smaller firms employing 10-to-200 workers. From 1991 to 2017, the SEPI Foundation has surveyed about 1,800 firms each year and made an effort to minimize the sample deterioration due to either firms' exit or missing response.

Firms are assigned into 20 two-digit manufacturing industries that roughly match the NACE review 2 classification, and the survey contains a rich set of information about production process, sales, employment, cost and prices, technological adoption, and foreign trade. Crucially for my purposes, the ESEE data report firms' equity

[11]The AMNE reports MNEs' production levels by country of origin. However, there is no distinction between vertical and horizontal FDI.

[12]Previous studies praise the reliability and accuracy of these data (Guadalupe et al., 2012; Doraszelski and Jaumandreu, 2013, 2018; Koch and Smolka, 2019; Stapleton and Webb, 2020; Koch et al., 2021).

composition and robot adoption choices. Following the International Monetary Fund (2007), I define a firm as foreign-owned if a company headquartered outside of Spain owns at least 10% of its capital. In terms of robot adoption, the survey asks firms "[...] whether their production process uses any of the following systems: 1. Computer-digital machine tools; 2. Robotics; 3. Computer-assisted design; 4. Combination of some of the above systems through a central computer (CAM, flexible manufacturing systems, etc.); 5. Local Area Network (LAN) in manufacturing activity". Based on the answer to this question, the SEPI Foundation constructs a binary indicator equal to 1 if a firm employs "Robotics" in a given year and 0 otherwise.[13]

Notwithstanding this richness, the ESEE data also come with some limitations. First, firms do not disclose the identity of their foreign owners.[14] Second, the survey does not contain information about whether a firm is owned by a multinational company with headquarters in Spain. Finally, robot adoption information is only available at the extensive margin. The first limitation prevents analyzing otherwise interesting potential sources of heterogeneity. For example, one may conjecture that parents headquartered in places where robots are highly diffused are more likely to spur robot adoption than parents located elsewhere. Similarly, vertical and horizontal FDI may produce different effects. The second limitation prevents analyzing, for instance, if being acquired by a Spanish or foreign multinational delivers different robot adoption outcomes. Finally, the third limitation prevents studying the intensive margin of robot adoption and the effect of foreign ownership on different categories of industrial robots.[15] Hopefully, more data will become available to inspect these differences in the future.

Data Cleaning and Sample Selection. I restrict my attention to the years between 1993 and 2014. I exclude years before 1993 to match the starting date of the IFR data. This choice also circumvents minor sample inconsistencies between the 1990 and subsequent survey waves. I exclude years after 2014 because robot adoption information is not available after that year.

I impose four sample selection criteria. First, I remove all firms that do not answer the survey for at least two consecutive years. I do so to avoid potentially non-random sample attrition. Second, I remove domestic firms that are involved in domestic mergers or divestitures during the sample period.[16] Third, I remove Spanish firms that own

[13] Although industrial robots are not explicitly mentioned, Koch et al. (2021) show that robot adoption patterns in the ESEE data are consistent with the industry-level trends reported by the IFR.

[14] To be clear, if a firm is owned by a foreign company, the data only report the share of equity under foreign control.

[15] There are six types of industrial robots: articulated robots, SCARA (selective compliance assembly robot arm) robots, Cartesian robots, and parallel robots (International Federation of Robotics, 2019).

[16] The ESEE data contain explicit information about these changes. See Section 5.3, Other Types of Acquisitions for further details.

equity share of companies located abroad (i.e., perform "outward FDI").[17] Fourth, I remove firms that are always foreign-owned or switch from domestic to foreign ownership multiple times. This criterion excludes greenfield FDI or firms already foreign-owned in 1993. Therefore, the final sample only includes always domestic-owned firms and firms that switch at most once from domestic to foreign ownership from 1994 onward.

One outstanding feature of the survey is that the robot adoption indicator is only available in eight years (1990, 1991, 1994, 1998, 2002, 2006, 2010, and 2014). Because the foreign ownership indicator has a yearly frequency, it is crucial to have the robot adoption indicator every year to study how switching ownership affects the likelihood of employing robots. I address this issue by filling robot adoption information forward between two consecutive non-missing survey answers.[18] For instance, if a firm employs robots in 1994, I assume it also does it in 1995, 1996, and 1997. I update the indicator in 1998 based on the actual survey answer in that year and fill it forward until 2001 using the same criterion. I repeat this procedure in 2002, 2006, and 2010. For consistency, I impute the 1993 indicator with its value in 1991. Before imposing this criterion, about 65% of firm-year robot adoption information is missing. After, only about 8% is still missing. These are a few cases in which firms do not answer in two consecutive waves.

I also fill in missing values in the ownership structure and other ESEE variables. I interpolate missing values in the foreign ownership indicator using the same forward criterion I adopt for robot adoption. However, information about foreign ownership is available every year, and the share of missing observations in the sample is less than 1%. I also use the same rule to fill in missing values in other dichotomous indicator variables available every four years (e.g., other automation-type non-robotic technology adoption, manufacturing process, and exporter status). I replace missing values in the continuous variables (e.g., sales, employment, cost and prices, investment, physical inputs, etc.) with their average between two consecutive non-missing years, but I only do it if the length of the missing spell is shorter than three years.

Finally, I deflate nominal variables using firm-level or industry-level deflators. The ESEE provides a Paasche-type index that measures the average output price change between two consecutive periods for each active firm. It accommodates both mono and multi-product firms, and I use it to deflate firms' sales. I deflate physical inputs, R&D expenditure, wages, and investment using the one-digit manufacturing deflator from the *Instituto Nacional de Estadística* (INE). I use 2006 as the baseline year.

[17] 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 in, say, 1997 starts doing outward FDI in, say, 2003, I exclude it from the sample.

[18] Forward imputation is consistent with the empirical finding that robot adoption is a lumpy investment (Humlum, 2021).

Sample Description. The final sample contains 3611 firms. Among them, 123 become foreign-owned at some point in time. Table A.1 shows summary statistics (mean and standard deviation) by ownership type using firms' lifetime characteristics. Therefore, for foreign-owned firms, I pool together pre and post-acquisition periods. Panel A reports summary statistics about the adoption of robots and other automation-type non-robotic technology (i.e., numerically controlled machines, CAD manufacturing, and flexible systems), whereas Panel B about the type of manufacturing production (i.e., batch, mass, continuous, and mixed manufacturing). Panels C and D contain information about firms' effort to acquire foreign technology and innovation activity, respectively. Finally, Panel E reports standard information about domestic and overseas activities (e.g., exports, number of export markets, wages, employees, investment, physical inputs, sales, and labor productivity). Table A.2 contains the description of each variable.

Although foreign-owned firms are only the 3% of the total, they outperform, on average, domestic-owned ones in each dimension. They are more productive, innovative, sell more, employ more workers, pay higher wages, and engage more in international trade than domestic firms indeed. However, because Table A.1 is constructed using firms' lifetime characteristics, it subsumes both foreign ownership selection and treatment effects. To inspect pre-acquisition differences, Figure A.1 shows the empirical probability density function (p.d.f.) of the log of employees, sales, physical inputs, R&D expenses, wages, and investment by ownership type. As in Table A.1, I estimate the empirical p.d.f. for domestic-owned firms based on their lifetime characteristics. However, unlike in Table A.1, I only estimate it for the years before the acquisition date for foreign-owned ones.

Overall, Figure A.1 illustrates that to-be-acquired firms outperform always domestic-owned ones already before acquisition. This regularity is well-known in the literature (Guadalupe et al., 2012; Koch and Smolka, 2019; Bircan, 2019; Setzler and Tintelnot, 2021; Alfaro-Ureña et al., forthcoming). In Section 5, I will account for selection into foreign ownership to identify the effect of switching from domestic to foreign ownership on robot adoption.

4 Cross-Country Industry-Level Evidence

In what follows, I explore the relationship between multinational production (i.e., the gross output produced by foreign-owned firms) and robot adoption across countries and industries.

4.1 Multinational Production and Robot Adoption

The theoretical correlation between multinational production and robot adoption is ambiguous. Most FDI worldwide are vertical and, especially in the manufacturing sector, exploit production cost differences across countries (Antras and Helpman, 2004). As long as recipient countries are characterized by low wages, the robot adoption incentives are low in those places. From this viewpoint, one expects to find a negative correlation. However, foreign investors also care about the destination countries institutional quality, market size, technological level, and macroeconomic stability (Jardet, Jude and Chinn, 2022), which may also favor robots' diffusion. From this viewpoint, one expects to find a positive correlation.

The data favor the second hypothesis. Figure B.1 shows the average correlation between the log of the number of robots and the log of multinational production by country (across industries and years). The correlation is positive in most countries, the sample average is about 30%, and it is strongest in China, where it peaks at about 60%. Figure B.2 shows the linear fit of a regression of the log of the number of robots per thousand employees, which is a standard measure of robots' diffusion (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020), on the log of multinational production at the country-industry-year level. The estimated coefficient is about 0.5% and is significant at the 1% level. To further inspect the correlation between multinationals' activities and robot adoption, I estimate the following equation:

$$\log\left(R/N\right)_{cit} = \beta \log(MP)_{cit} + \mathbf{X}_{cit-1}\boldsymbol{\delta} + \eta_{cy} + \eta_{iy} + \varepsilon_{ciy}. \tag{1}$$

$\log\left(R/N\right)_{cit}$ is the log of the number of robots per thousand employees in country c's industry i in year t. $\log(MP)_{cit}$ is the log of gross output produced by foreign-owned firms in country c's industry i in year t. $\mathbf{X}_{cit-1}$ is a matrix of time-varying country-industry level controls. It includes the one-year lag of the log of the capital-to-labor employment ratio and the interest rate-to-wage ratio. These variables control for country-industry level time-varying differences in relative production factor employment levels and prices, respectively. Finally, η_{cy} and η_{iy} capture any time-varying country and industry-level shocks potentially correlated with $\log(MP)_{cit}$. For instance, they account for the fact that countries or industries growing at different rates may experience heterogeneous patterns of robot adoption and multinationals' activity.

Table 1 reports the results. Column (1) shows the estimates without time-varying country-industry level controls, which I progressively add in Columns (2) and (3). The rightmost column contains the full specification and reports an estimate of about 0.28%, which is about half of the unconditional one in Figure B.2. As expected, Columns (2) and (3) show that robots' diffusion is more prominent where capital is more abundant (i.e., the capital-to-employee ratio is higher) and cheaper (i.e., the interest rate-to-wage ratio is lower) than labor.

Table 1: Cross-Country Industry-Level Correlations

Dependent Variable:	Log(Robots/Thousand Employees)$_{cit}$		
	(1)	(2)	(3)
Log(Multinational Production)$_{cit}$	0.28***	0.27***	0.28***
	(0.03)	(0.03)	(0.03)
Log(Capital Stock/Thousand Employees)$_{cit-1}$		0.13***	0.17***
		(0.04)	(0.04)
Log(Interest Rate/Wages)$_{cit-1}$			-0.10**
			(0.04)
Industry-Year FE	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes
Observations	6,563	5,870	5,744
Estimator	OLS	OLS	OLS

Note: The unit of observation is a country-industry-year tuple. Log(Robots/Thousand Employees)$_{cit}$ is the log of the number of robots per thousand employees in country c's industry i in year t. Log(Multinational Production)$_{cit}$ is the log of gross output produced by foreign-owned firms in country c's industry i in year t. Log(Capital Stock/Thousand Employees)$_{cit}$ is the capital stock per thousand employees in country c's industry i in year t. Log(Interest Rate/Wages)$_{cit}$ is the ratio between the capital interest rate and gross wages in country c's industry i in year t. Heteroscedasticity-robust standard errors in parenthesis. Significance levels: *** 0.01, ** 0.05, * 0.1.

Table B.2 shows that the baseline results are robust to omitting the top five robotized countries in the sample (i.e., China, Germany, Japan, South Korea, and the United States) and the automotive industry, which accounts for over 80% of the total worldwide robot stock in any sample year. This result strengthens the confidence about the robustness of the correlation in Table 1. Finally, in Appendix B.3.1 I show that a qualitatively similar pattern also holds using a long-difference specification, which builds confidence that the baseline results do not merely pick up pre-sample trends.[19]

5 The Foreign Ownership Robot Adoption Premium

The cross-country evidence highlights a positive and robust correlation between multinational production and robot adoption. However, reverse causality and omitted variable bias prevent a causal interpretation. To make further progress in understanding whether becoming foreign-owned affects the probability of robot adoption, I exploit

[19] In an unreported specification, I re-estimated equation (1) using only multinational production from the top five robotized countries in the sample. The idea was to check if FDI coming from highly robotized countries correlated more strongly with robot adoption in the destination. However, I found no evidence in favor of this hypothesis.

the ESEE firm-level data. First, I provide descriptive evidence about the relationship between foreign ownership and robot adoption at the firm-level. Second, I deal with selection and estimate how switching to foreign ownership increases the probability of employing robots (i.e., the foreign ownership robot adoption premium). Third, I evaluate the explanatory power of different mechanisms consistent with the results.

5.1 Foreign Ownership and Robot Adoption: A First Look

Figure A.2 shows how robot adoption has evolved by ownership type. Although the proportion of robot adopters has nearly doubled in both sub-samples over time, the share of robot adopters in any given year among foreign-owned firms is about twice as large than among domestic-owned ones. Figure A.3 shows that a similar pattern applies in the cross-section across industries. The fact that foreign-owned firms are systematically more likely to employ robots than domestic ones is new in the literature.

To move towards quantifying the foreign ownership robot adoption premium, I estimate the following event-study specification:

$$R_{f(j)t} = \sum_{s=-\underline{s}}^{\bar{s}} \theta_s O^s_{ft} + \mathbf{X}_{ft-1}\boldsymbol{\beta} + \alpha_f + \alpha_{jt} + \varepsilon_{f(j)t}. \tag{2}$$

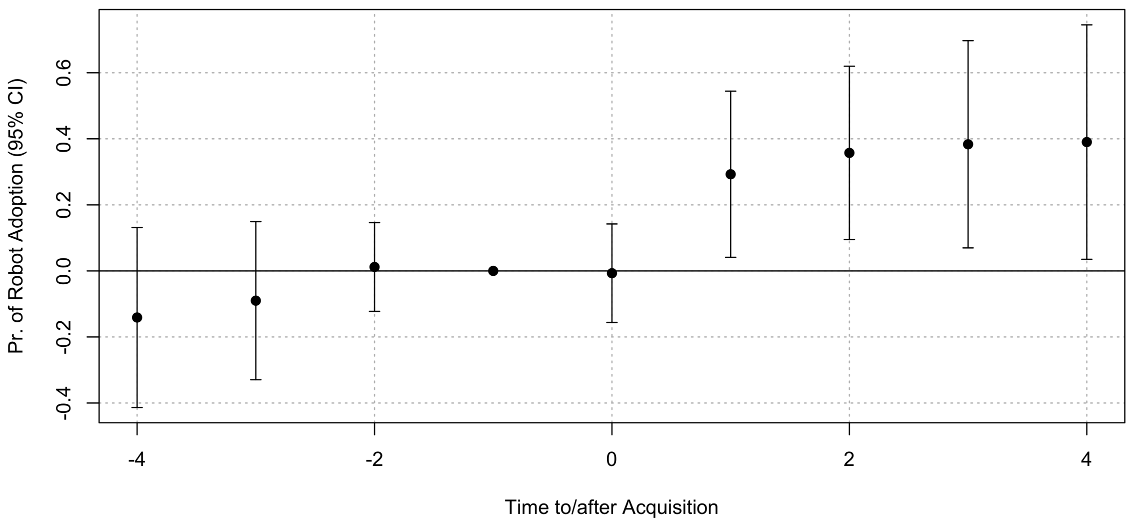
$R_{f(j)t}$ is a dummy equal to one if firm f in industry j employs a robot in year t and zero otherwise. The event-time dummy is $O^s_{ft} := \mathbf{1}\{t = \tau_f + s\}$ for $s \in \{-\underline{s}, \dots, \bar{s}\}$. $\mathbf{1}\{\dots\}$ is an indicator function, and τ_f is the year in which firm f is acquired. Therefore, O^s_{ft} is a dummy identifying the periods before or after the foreign acquisition date. I saturate the model by defining $O^{\bar{s}}_{ft} := \mathbf{1}\{t > \tau_f + \bar{s}\}$ and $O^{\underline{s}}_{ft} := \mathbf{1}\{t < \tau_f - \underline{s}\}$. I set $\underline{s} = \bar{s} = 5$. I also normalize $\theta_{-1} = 0$. $\mathbf{X}_{ft-1}$ is matrix of firm-year level controls. It includes one, two, and three-year lags of (the log of) firm sales and the one-year lag of sales' growth rate. These controls account for observed time-varying differences in size and performance among firms. Finally, α_f and α_{jt} denote firm, respectively industry-year, fixed effects.

I estimate equation (2) only using the sub-sample of the 123 ownership switchers. The event-study coefficients θ_s are identified using within-firm variation after controlling for firm-level time-varying observed differences and industry-level (possibly time-varying) common shocks to all firms. The identifying assumption is that, after including such controls, not-yet-acquired firms are a credible counterfactual for acquired ones.[20] Figure 1 shows the results. As of the first year after the acquisition date, new affiliates

[20] I also estimate equation (2) including never acquired firms in the control group. In this case, the identifying assumption is that, after including the controls on the right-hand side of equation (2), both not-yet-acquired and never acquired firms constitute a credible counterfactual for acquired ones. Figure C.1 shows the results, which are qualitatively similar to the baseline.

become about 35%, on average, more likely to employ robots than in the year before the acquisition. There are no statistically significant pre-trends at any conventional statistical level.

Figure 1: Event-Study



Note: The Figure plots the estimates (and the 95% confidence intervals around them) that I obtain from equation (2). The unit of observation is a firm-year pair, and I cluster standard errors by firm. I restrict the sample to the subset of acquired firms. Starting from the first year after the acquisition date, new affiliates become about 35% more likely to employ robots than in the year before the acquisition.

Several recent papers have shown that estimating event-study specifications like equation (2) with a two-way fixed-effects estimator may fails to recover the treatment effect of interest even if assignment into treatment is random.[21] This happens when the treatment roll-out is staggered and the treatment effects evolve over time. Intuitively, the inclusion of already treated units in the control group for some cohorts gives rise to a "forbidden comparison" (Borusyak et al., 2021), and the two-way fixed effects estimator delivers variance-weighted averages of heterogeneous treatment effects which are hard to interpret.

In my setting, this concern is warranted if the probability of robot adoption varies over time depending on the acquisition year. To deal with this issue, I use the method proposed by Sun and Abraham (2021) and estimate cohort-specific dynamic treatment effects, which I then aggregate using the size of each cohort as weight. Figure C.2 shows

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

the results. Overall, the two figures deliver a qualitatively similar pattern and, except for the first year post-acquisition, statistically equal estimates at the 5% level.

5.2 The Effect of Foreign Ownership on Robot Adoption

Empirical Strategy. Although suggestive of a causal relationship, the estimates in Figure 1 may be contaminated by selection effects. In particular, one may worry that unobserved firm-level transitory shocks that correlate with foreign acquisition may also drive robot adoption (Blundell and Costa Dias, 2009). For instance, some firms may foresee the foreign acquisition and, therefore, restructure their operations and investment (in robots or other complementary technologies) already before the event. Whereas the absence of pre-trends in Figure 1 holds back this hypothesis, I explicitly deal with this concern in what follows.

The ideal way to address this issue would be to randomly assign foreign ownership to domestic firms and see how their robot adoption choices change, if at all. Unfortunately, this approach is unfeasible. To make progress, I use an inverse propensity score reweighing (IPRW) estimator à la Guadalupe et al. (2012).[22] This procedure combines a difference-in-differences approach with a propensity score reweighing procedure, and compares changes in robot adoption of acquired firms with those of similar firms that remain under domestic control.

The estimator works in two stages. In the first stage, I estimate the probability that each firm is acquired by a foreign company based on an exhaustive set of firms' observable characteristics in levels and growth rates.[23] To do so, from 1994 to 2014, I include firms acquired in that year in the treatment group and firms that are always domestic-owned in the control group. Then, I stack together treated and control firms across all years and estimate, for each firm, the probability of becoming foreign-owned as a function of the following variable: sales' growth rate, log sales, log number of employees, log wages, log investment, log physical inputs, log R&D expenses, log exports, and number of export markets.[24] All variables refer to the one-year lag before the acquisition date, and I call them "selection controls". Because of missing values, I can

[22]A number of papers building upon Guadalupe et al. (2012) also employ this estimator (Koch and Smolka, 2019; Koch et al., 2021). My implementation of the estimator closely follows the standard practice in this literature. DiNardo, Fortin and Lemieux (1996) show that the IPRW estimator has better finite sample properties than other matching techniques such as propensity score matching.

[23]The purpose to account for all the relevant time-varying observed determinants that predict foreign acquisition at the firm level (Guadalupe et al., 2012; Koch and Smolka, 2019).

[24]Table C.1 shows first-stage probit regressions adding one variable at a time. The rightmost column of the Table highlights that firms are more likely to become foreign-owned if they are growing faster than average (i.e., with a higher growth rate of sales between the acquisition year and the one before), are larger (i.e., employ more employees than average), more innovative (i.e., spend more on R&D than average), and export more.

successfully compute the propensity score only for 79 out of 123 total foreign-owned firms.[25] As Guadalupe et al. (2012), I also exclude from the control group firms that do not fall within the common support. Then, I assign a weight of $1/\widehat{p}$ to acquired firms and of $1/(1-\widehat{p})$ to non-acquired one, being $\widehat{p}$ the estimated first-stage probability (i.e., the propensity score). This reweighing scheme aims at making the two groups of firms comparable on observables before the acquisition.[26]

In the second stage, I estimate the following equation on the reweighed sample:

$$R_{f(j)t} = \theta O_{ft} + \alpha_f + \alpha_{jt} + \varepsilon_{f(j)t}. \tag{3}$$

Notation follows from equation (2). The main differences with equation (2) are that I suppress time-varying firm-level controls ($\mathbf{X}_{ft-1}$) and estimate a single value for the foreign ownership robot adoption premium (θ). The identifying assumption is that, post-reweighing and after controlling for the included fixed effects, treatment is random. Under this assumption, the IPRW estimator identifies the effect of becoming foreign-owned on the probability of robot adoption (i.e., the foreign ownership robot adoption premium).

Results. Table 2 reports the results of estimating equation (3). For comparison, Columns (1) and (2) show the OLS estimates without, respectively with, firm and industry-year fixed effects. Column (1) shows an unconditional estimate for θ of about 28%, whereas accounting for firm fixed effects and industry trends delivers an estimate of about 11%. Column (3) shows the results when including all the selection controls as additional regressors. In this case, the estimated average coefficient is about 12%. Column (4) shows the results using the IPRW estimator, which I consider the preferred specification. The estimates reveal that, post-acquisition, affiliates are about 10% more likely to employ robots than comparable domestic producers.[27] Although the estimates in Columns (2), (3), and (4) are not statistically different from each other, the OLS point estimates are slightly upward-biased, consistently with positive self-selection into foreign ownership.

[25] As a robustness check, I also re-estimated the propensity score only as a function of lagged log sales and lagged log number of employees. In this case, I can estimate it for all firms in the treatment group. Using this procedure, I estimate an average premium of 9%, which is statistically indistinguishable from that in the rightmost column of Table 2.

[26] Table C.2 shows that, before reweighing, I always reject the hypothesis that the treatment and control group have the same average characteristics at any conventional statistical level. After reweighing, I never reject it at the 1% significance level.

[27] For benchmarking, the average probability that a firm employs robots in the sample is about 17%. The estimated premium about 58% of it.

Table 2: Firm-Level Baseline Regressions

Dependent Variable:	Robot_{ft}			
	(1)	(2)	(3)	(4)
$\text{Foreign-Owned}_{ft}$	0.28^{***}	0.11^{*}	0.12^{*}	0.10^{**}
	(0.05)	(0.06)	(0.07)	(0.05)
Firm FE	No	Yes	Yes	Yes
Industry-Year FE	No	Yes	Yes	Yes
Selection Controls	No	No	Yes	No
Observations	21,010	21,010	19,561	18,520
Estimator	OLS	OLS	OLS	IPRW

Note: The unit of observation is a firm-year pair. Robot_{ft} is a binary variable equal to 1 if firm f employs a robot in year t and 0 otherwise. $\text{Foreign-Owned}_{ft}$ is a binary variable equal to 1 if firm f is foreign-owned in year t and 0 otherwise. Selection controls include the one-year lag of sales' growth rate, log sales, log number of employees, log wages, log investment, log physical inputs, log R&D expenses, log exports, and number of export markets. In Column (4), I reweigh acquired firms by $1/\widehat{p}$ and non-acquired ones by $1/(1-\widehat{p})$, being $\widehat{p}$ the estimated probability of becoming foreign-owned. Cluster standard errors by firm in parenthesis. Significance levels: *** 0.01, ** 0.05, * 0.1.

Finally, Figure C.3 plots the dynamic estimates that I obtain by estimating equation (2) on the reweighed sample. The main difference with the baseline specification is that I drop the selection controls on the right-hand side of the equation and apply the inverse probability reweighing scheme instead. Whereas Figure C.3 delivers similar post-acquisition patterns as Figure 1, the reweighing procedure further assuages pre-acquisition anticipation effects. This result strengthens the interpretation of the premium and clarifies the role of foreign ownership in spurring robot adoption. Despite the fact that the adoption of robots is a growing phenomenon, MNEs accelerate and spread it.

Heterogeneity. Even if all firms experienced the same ownership shock, they might respond differently depending on their specific activity and surrounding environment. In what follows, I investigate if the premium depends on the degree of robots' diffusion in a given industry. This heterogeneity is relevant to understand if some sectors may be more exposed to the outcomes of multinational-induced robot adoption, which I discuss in Section 6.

I proxy industry-level robot adoption as follows. First, I compute the number of industrial robots deployed in each Spanish manufacturing industry in 1993. I choose this year because it is the first available one in the IFR data and to prevent the measure from being affected by robot adoption from 1993 onward.[28] Second, I group industries

[28] I follow Koch et al. (2021)'s cross-walk tables to match IFR and ESEE industry codes.

into terciles.[29] The first tercile contains industries characterized by a low initial robot adoption stock (e.g., manufacture of coke and pharmaceutical), whereas the last tercile contains industries characterized by a high initial robot adoption stock (e.g., automotive and electronics). The second one includes those in the middle (e.g., textiles).

Column (1) of Table C.3 reports the results of equation (3) when interacting the foreign-ownership binary indicator with my industry-level proxy of robot adoption.[30] The estimates reveal that the premium is about 27% for firms in the first tercile. This figure is about three times larger than the baseline estimate. Firms in the second tercile report a premium of 13% instead, which is statistically indistinguishable from the baseline one. Finally, I do not reject the hypothesis that the premium for firms in the last tercile is nil. Columns (2), (3), and (4) show the results when estimating equation (3) on each sub-sample separately. The results are consistent with Column (1). Overall, the estimates suggests that initially less robotized sectors are more exposed to multinational-induced robotization and, potentially, to its implications.

5.3 Why Do Foreign Ownership Boosts Robot Adoption?

Alternative Hypotheses. Different mechanisms may explain why switching from domestic to foreign ownership boosts robot adoption. For instance, previous literature using the ESEE data shows that the possibility of expanding the customer base into foreign markets through the network of the parent is a central driver of product and process innovation (Guadalupe et al., 2012) and skill upgrading (Koch and Smolka, 2019). To the extent that robot adoption is complementary to these activities and allows to increase production and expand in global markets, the foreign market access channel is also relevant in my context.

An alternative hypothesis is that foreign acquisitions alleviate credit constraints, thus allowing firms to move closer to their first-best investment level (Harrison and McMillan, 2003; Manova et al., 2015). Another possible explanation is that foreign parents directly transfer knowledge about robot adoption (or other complementary inputs) to their affiliates. Indeed, technology flows within multinational networks are extensively documented in the literature (Branstetter et al., 2006; Keller and Yeaple, 2013; Bilir and Morales, 2020).

In what follows, I exploit the richness of the ESEE survey to evaluate the importance

[29] The first tercile includes 211 firms (11 of which become foreign-owned), the second one includes 1472 firms (35 of which become foreign-owned), and the third one includes 717 firms (31 of which become foreign-owned). I choose terciles to ensure there are enough foreign-owned firms in each bin. However, I find qualitatively similar results when using, e.g., quartiles.

[30] The inclusion of industry-trends in equation (3) accounts for any other industry-level, possibly time-varying, characteristics (e.g., share of tasks that can be performed by robots) that may also affect the size of the premium.

of these three mechanisms. I proceed in two steps. First, I test whether switching to foreign ownership is associated with increased foreign market access, reduced credit constraints, and technology transfers. Second, I evaluate the explanatory power of these three channels for robot adoption.

Testing Mechanisms. To study whether switching from domestic to foreign ownership grants access to foreign markets, credit, or superior technology, I estimate again equation (3) but replace the robot indicator on the left-hand side with variables related to the three mechanisms I evaluate.

To measure whether a firm has access to foreign markets via its foreign parent network, I exploit a question in the ESEE survey that asks firms by what means they access export markets. The possible answers are that they export via their foreign parents (either using their distribution channel or directly selling to them), their own means, specialized intermediaries, collective actions, or other means. Based on the answer to this question, the SEPI Foundation constructs a binary indicator equal to 1 if a firm exports via its foreign parent in a given year and 0 otherwise. The variable is only defined for exporters and, by construction, is always zero for domestic-owned firms. I use this variable as a proxy for foreign market access.

To evaluate if credit constraints prevent robot investment, I test whether acquired firms increase their external R&D expenditures per worker, an activity typically subject to credit constraints (Brown et al., 2012).[31] Finally, although thoroughly testing for technology transfers would require (unfortunately unavailable) data about intra-firm activities, the ESEE reports firm expenditure on licenses and technical aid from abroad, which I use to proxy technology transfers. In particular, I define a variable equal to 1 if a firm imports foreign technology in a given year and 0 otherwise. Then, I check if acquired firms are more likely to import technology from abroad, possibly from their parents, than domestic firms.

Table 3 shows the results. Column (1) shows that, conditional on exporting, acquired firms are about 44% more likely to do it via their foreign parental network than any other means. By contrast, they do not increase their external R&D per employee (Column 2) and are not more likely to import foreign technology (Column 3), which holds back the credit constraints and technology transfers hypotheses.

To provide further evidence about affiliates' expansion into global markets following the acquisition date, Figure C.4 shows the event-study results that I obtain by estimating equation (2) on the reweighed sample and using Exp. via Foreign Parent$_{ft}$ as outcome variable. Consistently with Table 3, there is a sharp increase in the probability of exporting via the foreign parental network in the first four years after the acquisition

[31] I obtain similar results if I use, e.g., external R&D expenditures over total investment or sales.

Table 3: Firm-Level Mechanism Regressions (Step One)

Dependent Variables:	Exp. via Foreign Parent$_{ft}$	Log(Ext. R&D/Employees)$_{ft}$	Imp. of Foreign Tech.$_{ft}$
	(1)	(2)	(3)
Foreign-Owned$_{ft}$	0.44***	0.01	0.03
	(0.07)	(0.39)	(0.02)
Firm FE	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes
Observations	3,084	20,510	20,526
Estimator	IPRW	IPRW	IPRW

Note: The unit of observation is a firm-year pair. Exp. via Foreign Parent$_{ft}$ is binary variable equal to 1 if firm f exports via its foreign parental network at time t and 0 otherwise. Log(Ext. R&D/Employees)$_{ft}$ is the log of one plus the expenditure on external R&D per employee. Hence, it accounts both for the intensive and extensive margin of external R&D. Imp. of Foreign Tech.$_{ft}$ is binary variable equal to 1 if firm f imports licenses and technical aid from abroad at time t and 0 otherwise. Foreign-Owned$_{ft}$ is a binary variable equal to 1 if firm f is foreign-owned in year t and 0 otherwise. In all columns, I reweigh acquired firms by $1/\widehat{p}$ and non-acquired ones by $1/(1-\widehat{p})$, being $\widehat{p}$ the estimated probability of becoming foreign-owned. Cluster standard errors by firm in parenthesis. Significance levels: *** 0.01, ** 0.05, * 0.1.

date. I also estimate the same specification using the log of exports as outcome variable. Figure C.5 shows that, post-acquisition, affiliates increase by about 30% their exports compared to the year before the acquisition. Hence, the possibility of exporting via the foreign parental network is also associated with an increase in the overall volume of exports. There are no pre-trends at the 5% level in both cases.

Next, I evaluate which of these three mechanisms, if any, has the largest explanatory power for robot adoption. To do so, I estimate again equation (3) but replace the binary indicator for foreign ownership on the right-hand side with the three proxies for the mechanisms of interest, which I add progressively.

Table 4 shows the results. Column (1) shows that firms that access export markets via their foreign parental network are about 17% more likely to employ robots than those that export via any other channel.[32] Columns (2) and (3) show that this estimate is robust to including my proxies for credit constraints and import of foreign technology, which do not significantly correlate with robot adoption.

To summarize, the results point out to the following mechanism. Upon acquisition, affiliates have the chance of expanding their customer base abroad thanks to their foreign parental network. However, firms need to scale-up production to translate higher potential demand into actual sales, and robot adoption is one way to achieve this result. This results is also consistent with previous literature showing that the ability to serve foreign markets is a crucial driver of technology adoption and innovation (Lileeva and Trefler, 2010; Bustos, 2011).

[32] To be clear, the treatment group includes acquired firms exporting via their foreign parent, whereas the control group contains domestic-owned exporters and acquired firms that do not export via their foreign parent.

Table 4: Firm-Level Mechanism Regressions (Step Two)

Dependent Variable:		Robot_{ft}	
	(1)	(2)	(3)
Exp. via Foreign Parent_{ft}	0.17**	0.18**	0.17**
	(0.08)	(0.08)	(0.08)
$\text{Log(Ext. R\&D/Employees)}_{ft}$		-0.002	-0.002
		(0.005)	(0.005)
Imp. of Foreign Tech._{ft}			0.09
			(0.08)
Firm FE	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes
Observations	3,080	3,074	3,074
Estimator	IPRW	IPRW	IPRW

Note: The unit of observation is a firm-year pair. Exp. via Foreign Parent_{ft} is binary variable equal to 1 if firm f exports via its foreign parental network at time t and 0 otherwise. $\text{Log(Ext. R\&D/Employees)}_{ft}$ is the log of one plus the expenditure on external R&D per employee. Hence, it accounts both for the intensive and extensive margin of external R&D. Imp. of Foreign Tech._{ft} is binary variable equal to 1 if firm f imports licenses and technical aid from abroad at time t and 0 otherwise. $\text{Foreign-Owned}_{ft}$ is a binary variable equal to 1 if firm f is foreign-owned in year t and 0 otherwise. In all columns, I reweigh acquired firms by $1/\widehat{p}$ and non-acquired ones by $1/(1-\widehat{p})$, being $\widehat{p}$ the estimated probability of becoming foreign-owned. Cluster standard errors by firm in parenthesis. Significance levels: *** 0.01, ** 0.05, * 0.1.

The Heterogenous Effects of Increased Market Access. Table C.4 digs deeper into the role of exporting via the foreign parent. In particular, I run again the specification in Column (1) of Table 4 but interact Exp. via Foreign Parent_{ft} with binary indicators of previous ownership (Column 1), export status (Column 2), and both previous ownership and export status (Column 3).

Column (1) shows that firms that access export markets via their foreign parental network in the same year that they are acquired are about 30% more likely to employ robots than acquired firms that export via other means.[33] This figure is 8 p.p. lower for firms that access export markets via their foreign parent in the current period but were already foreign-owned in the previous one.[34] Consistently with Table 2, being foreign-owned in the previous year also correlates with robot adoption in the current one.

Column (2) shows that exporting via the foreign parental network increases by

[33]Because only acquired firms can export via their foreign parental network, Exp. via Foreign $\text{Parent}_{ft} = 1$ and $\text{Foreign-Owned}_{ft-1} = 0$ denotes firms acquired in t that start exporting via the foreign parental network in that year.

[34]For this group, the estimated probability is $0.30 + 0.29 - 0.37 = 22\%$.

about 45% the probability of robot adoption for firms that did not export at all in the previous period. By contrast, this probability is about 30% for firms that were already exporting in the previous year.[35] Consistently with Koch et al. (2021), I also find that being an exporter positively correlates with the probability of robot adoption.

Finally, Column (3) shows that exporting via the foreign parents has the largest impact on robot adoption for firms that were not foreign-owned and did not export in the previous period. For them, the estimated probability of adoption is 46%. This probability is about 33% for firms that export via their foreign parent in the current period and were already foreign-owned but did not export in the previous one. A similar figure also applies to already exporting firms.[36]

Other Types of Acquisitions. One interesting question is whether different types of acquisitions, e.g., from a Spanish multinational or domestic firm, produce different robot adoption outcomes. Answering this question is relevant because it reveals whether policies promoting foreign investment may deliver different outcomes than those promoting, for instance, the activities of multinationals headquartered in the home country or domestic mergers. In principle, given the documented importance of increased market access through the parental network, I expect that being acquired by a Spanish multinational produces similar outcomes. Unfortunately, as already mentioned in Section 3.2, the ESEE survey does not report this information, which makes it unfeasible to evaluate this hypothesis.

However, the data do contain information about domestic mergers. In particular, each firm reports whether it changed legal status in a given year. There are six possible cases: (1) no change, (2) it has split, (3) it has acquired other firms, (4) it has born after a split process, (5) it is the result of a domestic merger process, or (6) it has changed the trademark and legal form. As in the baseline exercise, I include firms that never experience any change in the control group. However, I now include in the treatment group firms that are the result of a domestic merger process. There are 33 firms that meet this criterion.[37] Even if the size of the treatment group is limited, the ESEE data allow to follow these firms over time. Therefore, I can create a binary indicator equal to 1 if a firm was acquired by another Spanish company (i.e., it is the result of a domestic merger process) in year $s \leq t$ and 0 otherwise.

I estimate again equation (2) using this new sample. The only difference is that the O^s_{ft} dummy(-ies) identifies the periods before or after the domestic acquisition event.

[35] For this group, the estimated probability is $0.45 + 0.14 - 0.29 = 30\%$.

[36] For the first group, the estimated probability is $0.46 + 0.28 - 0.40 = 33\%$. For the second, it is $0.46 + 0.28 - 0.40 + 0.13 - 0.12 = 35\%$. However, these two estimates are not statistically different.

[37] As for future foreign-owned firms, Figure C.6 shows that to-be-acquired firms by a domestic company are a positively selected sub-sample of the population of Spanish manufacturing firms.

Figure C.7 shows that, post-acquisition, firms acquired by a domestic parent are not significantly more likely to employ a robot than in the year before the acquisition. To deal with similar identification concerns as in Section 5.2, I re-adapt and use again the IPRW estimator I described for equation (3).[38] Table C.6 shows the results. Whereas the OLS estimates deliver a statistically positive correlation between being acquired by a domestic company and robot adoption, the estimate becomes statistically indistinguishable from zero after controlling for selection using the IPRW estimator.

The previous discussion about the importance of foreign market access offers a potential explanation for this result. By definition, non-multinational Spanish parents do not provide their affiliates with access to global markets through their multinational network. Hence, domestic mergers may not grant a sufficiently higher demand level to justify paying the fixed cost of robot adoption.

5.4 Other Outcomes

Robots are rather expensive and sophisticated machines to use.[39] If foreign owners boost their adoption, it is plausible that they also restructure firms' production process more broadly. For instance, using a similar specification as in equation (3), Table C.7 shows that newly acquired firms become about 8% less likely to perform batch manufacturing, i.e., low-scale serial production, and about 6% more likely to engage in continuous manufacturing, i.e., 24/7 high-scale production activity. Although this type of production naturally lends itself to robot deployment, foreign ownership my also bring about other changes. In what follows, I investigate whether switching to foreign ownership boosts the adoption of other automation technology and, more in general, how firms' performance changes after the acquisition.

Other Automation Technology. One interesting question is whether firms acquired by a foreign company also become more likely to employ other automation technology beyond robots and, if so, which ones. Answering this question is useful to understand the nature of the technological plan that foreign parents have for their affiliates in Spain.

[38] In the first step, I estimate the probability of being acquired by another domestic firm as a function of the lagged (log of) number of employees, (log of) sales, (log of) wages, (log of) physical inputs, exporter status, sales and employment growth rate. Table C.5 shows that, after reweighing, I do not reject the hypothesis that the treatment and control group have the same average characteristics at the 1% significance level. Notice that the selection controls differ from the baseline exercise. I change them to achieve a better in-sample covariates' balance between groups than I would get using the same set of the main exercise. As a robustness check, I also compute the propensity score using the same selection controls as in the baseline exercise. Reassuringly, I obtain similar second-stage results.

[39] Acemoglu and Restrepo (2020) document that this cost ranges from about 44,000$ per robot to about 88,000$. These amounts are about 2% and 4% of the median annual sales value in the sample.

Thanks to the richness of the ESEE survey, I can use the same survey question that reports if a firm uses a robot (see Section 3.2) to construct binary indicators for whether firms employ computer-assisted design (CAD) manufacturing (i.e, a technology that allows doing computerized process design), numerically controlled machines (i.e., automatic machines that perform specific routine tasks), flexible design systems (i.e., computerized machines that help to connect robotic, CAD, and numerically controlled machines together), or any of those technologies. Whereas CAD manufacturing and flexible systems exhibit some complementarity with robots, numerically controlled machines should be understood as imperfect substitutes.[40] More in general, all these technologies are older, have lower labor-replacing potential, and scale-up firms' output less than robots do (Acemoglu and Restrepo, 2020).

I estimate equation (3) again but replace the robot adoption indicator with one of those new variables at a time. Table C.8 shows the results. Column (1) indicates that newly acquired firms become about 5% more likely to employ CAD manufacturing. However, Columns (2) and (3) show that they do not also become more likely to use numerically controlled machines or flexible systems. Finally, Column (4) shows that foreign acquisitions do not significantly spur the joint adoption of any of those automation-type non-robotic technologies.

Overall, these findings suggest that foreign parents deem robots to be different. Rather than investing in any automation-driven technology type, newly acquired firms only acquire the most advanced automation technology that allows them to scale-up operations more significantly. Whereas they may also decide to adopt complementary technology, there is no evidence that they invest in lower-quality substitutes.

Gains and Distributional Outcomes. The results documented so far suggest that foreign ownership generates substantial gains for acquired firms (e.g., enabling production scale-up to expand in the global market). An interesting question is how conspicuous are these gains and whether they are evenly shared within the firm.

To answer these questions, I estimate again equation (3) but use several measures of firm performance as outcome variables. Table C.9 reports the results.[41] The first four columns reveal that switching to foreign ownership induces sizable firm-level gains. Column (1) shows that, upon acquisition, firms increase sales by by about 37%, whereas Columns (2) and (3) show that they also increase employment and wages by 22%, respectively 9%.[42] Labor productivity grows by about 12% after the acquisition (Column

[40] The main advantage of robots is that they can be reprogrammed to perform multiple tasks. By contrast, numerically controlled machines can usually perform a single task only.

[41] Notice that the outcomes are expressed in logs. Therefore, the average effect must be computed as $100 \times (\exp(x) - 1)\%$, being x the estimated coefficient.

[42] This wage premium is consistent with the estimates of Setzler and Tintelnot (2021) for the US.

4). However, Column (5) suggests that foreign acquisition does not evenly benefits all production factors. The ratio between sales and wages increases by about 23% indeed, so the labor share in revenues fall and firms tilt production towards capital-intensive activities.[43]

Overall, foreign acquisitions create both gains and distributional outcomes within firms. One interesting question is how much of these changes are due to robot adoption versus other forces. I address this question and discuss the industry-level implications of FDI and robot adoption in the next section.

6 The Implications of MNE-Induced Robotization

The previous results show that foreign-owned firms are more likely to deploy robotic technology. Whereas robot adoption boosts firm activities, it also redistributes income away from labor within firms. I leverage these insights to introduce a dynamic partial equilibrium model of firm investment based on Doraszelski and Jaumandreu (2018) and Humlum (2021), which I use to further investigate the aggregate gains and distributional consequences of multinational-induced robotization in the Spanish manufacturing industry during the sample period.

6.1 A Model of Foreign Ownership and Robot Adoption

Set Up. Firms employ physical inputs and labor with constant elasticity of substitution to produce final output. Their production function features labor-augmenting and total factor productivity.[44] Firms can be either domestic or foreign-owned. As in the previous section, foreign ownership is irreversible. If firm f is foreign-owned in year t, it will also stay under foreign ownership in any $\tau > t$. By contrast, domestic-owned firms in year t become foreign-owned with finite probability in the next period.[45]

Firms can invest in robots to maximize net (of the fixed robot adoption cost) profits (π_{ft}). I assume that current ownership and robot adoption choices affect future labor-augmenting and total factor productivity, which evolve according to an endogenous

[43]This result is consistent with a large body of past literature showing that foreign-owned firms are more capital intensive than domestic-owned ones (Koch and Smolka, 2019; Sun, 2020).

[44]I make this modeling choice following Doraszelski and Jaumandreu (2018), who show that the observed employment and price dynamics in Spanish manufacturing are more consistent with labor-augmenting rather than capital-augmenting technological change. However, the main insights of this section hold no matter the type of factor-biased productivity assumed.

[45]This choice is dictated by parents' anonymity in the ESEE data. Guadalupe et al. (2012) model foreign acquisition in the same way.

Markov process.[46] Let $\Omega_{ft} = \{w_{ft}, r_{ft}, B_{ft}, z_{ft}, O_{ft-1}, R_{ft-1}\}$ be firm f's state vector in year t. It includes current labor (w_{ft}) and physical inputs (r_{ft}) input prices, labor-augmenting (B_{ft}) and total factor (z_{ft}) productivity, past ownership structure (O_{ft-1}) and robot adoption choices (R_{ft-1}). Firms choose physical inputs (M_{ft}), labor (L_{ft}), and invest in robot adoption (R_{ft}).[47] Firm f's problem in year t reads:

$$V_t\left(\Omega_{ft}\right) = \sup_{\{M_{ft}\geq 0, L_{ft}\geq 0, R_{ft}\in\{0,1\}\}} \left\{\pi\left(\Omega_{ft}\right) + \beta\mathbb{E}_t\left[V_{t+1}\left(\Omega_{ft+1}\right)\right]\right\} \tag{4}$$

$$\text{s.t. } y_{ft} = z_{ft}\left(M_{ft}^{\frac{\sigma-1}{\sigma}} + B_{ft}^{\frac{1}{\sigma}} L_{ft}^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}, \quad \sigma > 0,\ \sigma \neq 1 \tag{5}$$

$$\log\left(B_{ft}\right) = \beta\left(\log\left(B_{ft-1}\right), R_{ft-1}, O_{ft-1}\right) + u_{ft} \tag{6}$$

$$\log\left(z_{ft}\right) = \zeta\left(\log\left(z_{ft-1}\right), R_{ft-1}, O_{ft-1}\right) + \xi_{ft} \tag{7}$$

The expectation in equation (4) operates over future productivity levels and ownership structure. The production function in equation (5) contemplates that physical inputs and labor are either gross complements, $\sigma \in (0,1)$, or gross substitutes, $\sigma > 1$.[48] Equation (5) also implies a different role of total factor (Hicks-neutral) and labor-augmenting productivity. While z_{ft} uniformly shifts output, B_{ft} changes the relative productivity of physical inputs and labor within the firm.

Equations (6) and (7) state that current productivity depends on its past value, ownership structure, and robot adoption choices. Moreover, both productivity types depend on a expected term (i.e., $\beta(\dots)$ and $\zeta(\dots)$), which firms rationally forecast in $t-1$, and random noise (i.e., u_{ft} and ξ_{ft}), which they do not observe in $t-1$. These random terms are by construction mean independent from $\beta(\dots)$ and $\zeta(\dots)$ and capture uncertainty in productivity growth.

Empirical Strategy. Taking the logarithm of the ratio between the first-order conditions with respect to M_{ft} and L_{ft} in equation (5) delivers:

$$\log\left(\frac{M_{ft}}{L_{ft}}\right) = \sigma\log\left(\frac{w_{ft}}{r_{ft}}\right) - \log\left(B_{ft}\right). \tag{8}$$

[46]This assumption parallels the standard learning-by-doing idea in the production estimation literature (De Loecker, 2013; Doraszelski and Jaumandreu, 2013, 2018).

[47]I treat physical inputs and labor as the only static inputs for simplicity. Doraszelski and Jaumandreu (2018) show that the model can be extended, at computational costs, to feature, e.g., dynamic inputs or substitutability between high-skilled and low-skilled labor.

[48]Humlum (2021) shows that equation (5) can be micro-funded using a task-based approach of firm production, which is the standard way to model robot adoption in the literature (Acemoglu and Restrepo, 2018a,b; Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020).

Equation (8) states that the firm-level physical inputs-to-labor ratio depends upon (*i*) relative factor prices, (*ii*) elasticity of substitution, and (*iii*) labor-augmenting productivity. An increase of w_{ft}/r_{ft} raises the physical inputs-to-labor employment ratio only if $\sigma > 1$ (gross substitutes), and it decreases it if $\sigma \in (0,1)$ (gross complements). A decrease of B_{ft} always shifts the physical inputs-to-labor upwards. Substituting equation (6) inside equation (8) delivers:

$$\log\left(\frac{M_{ft}}{L_{ft}}\right) = \sigma \log\left(\frac{w_{ft}}{r_{ft}}\right) - \beta\left(\log\left(B_{ft-1}\right), R_{ft-1}, O_{ft-1}\right) - u_{ft}. \tag{9}$$

Estimating factor-biased productivity in equation (9) requires addressing two challenges. First, r_{ft} and B_{ft-1} are unobserved. Second, although $\beta(\dots) \perp\!\!\!\perp u_{ft}$ by definition, relative input prices may still be correlated with u_{ft}. I address the first issue by assuming that physical inputs is perfectly mobile across firms within an industry, i.e., $r_{ft} = r_{jt}$.[49] I obtain an expression for $\log(B_{ft-1})$ by recursively substituting equation (8) inside equation (9). Then, I approximate the unknown function $\beta(\dots)$ with the following polynomial:[50]

$$\beta(\dots) \approx \underbrace{\sum_{s=0}^{4}\left(\log\left(\frac{M_{ft-1}}{L_{ft-1}}\right) - \sigma \log\left(\frac{w_{ft-1}}{r_{jt-1}}\right)\right)^{s}}_{=\ \log(B_{ft-1})} + \beta_1 R_{ft-1} + \beta_2 O_{ft-1}. \tag{10}$$

Equation (10) clarifies that σ enters non-linearly equation (9) via $\log(B_{ft-1})$. β_1 and β_2 measure the semi-elasticity of factor-specific productivity to past robot choices and ownership structure.

I address the second issue by instrumenting $\log\left(w_{ft}/r_{jt}\right)$ with $\log(L_{ft-1})$, i.e., past employment choices. Doraszelski and Jaumandreu (2018) show that this is a valid (excluded) instrument under the assumption that factor-biased productivity follows a first-order Markov process. I jointly estimate σ, β_1, and β_2 using a just-identified GMM estimator (Hansen, 1982). The three moment conditions I use are $\mathbb{E}\left[\log(L_{ft-1})u_{ft}\right] = 0$, $\mathbb{E}\left[R_{ft-1}u_{ft}\right] = 0$, and $\mathbb{E}\left[O_{ft-1}u_{ft}\right] = 0$. With a consistent estimate of σ and B_{ft}, I recover TFP by inverting equation (5):

$$\log(\widehat{z}_{it}) = \log(y_{ft}) - \frac{\widehat{\sigma}}{\widehat{\sigma}-1}\log\left(M_{ft}^{\frac{\widehat{\sigma}-1}{\widehat{\sigma}}} + \widehat{B}_{ft}^{\frac{1}{\widehat{\sigma}}} L_{ft}^{\frac{\widehat{\sigma}-1}{\widehat{\sigma}}}\right). \tag{11}$$

[49] The assumption that physical inputs are perfectly mobile across firms is standard when estimating factor-biased productivity (Raval, 2019; Oberfield and Raval, 2021).

[50] Polynomial approximations of this type are standard in the production function estimation literature (Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Doraszelski and Jaumandreu, 2013, 2018).

Since I deflate firms' sales with a Paasche-type output price change index, it measures quantity-based TFP. Finally, to identify the contribution of foreign-ownership and robot adoption on firm-level Hicks-neutral productivity, I parametrize $\log(z_{it})$ as follows:

$$\log(\widehat{z}_{ft}) = \zeta_0 + \zeta_1 \log(\widehat{z}_{ft-1}) + \zeta_2 R_{ft-1} + \zeta_3 O_{ft-1} + \xi_{ft}. \tag{12}$$

Sample Selection. Bringing the model to the data requires addressing one last issue. Namely, dealing with the remaining missing values in the cleaned sample I create in Section 3.2. I address this issue as follows. I bin the data into seven mutually exclusive time intervals [1993-1995], [1996-1998], [1999-2001], [2002-2004], [2005-2007], [2008-2010], and [2011-2014]. If a firm is foreign-owned at least once in a given time interval, I set $O_{ft} = 1$. If not, I set $O_{ft} = 0$. Similarly, If a firm employs a robot at least once in a given time interval, I set $R_{ft} = 1$. If not, I set $R_{ft} = 0$. I take the time average within each interval for the continuous variables (physical inputs, labor, sales, and wages) disregarding missing values.

6.2 Estimation Results

Table 5 shows the estimates I obtain from equation (9). For benchmarking purposes, Column (1) and (2) report the OLS, respectively GMM, estimates when setting $\beta_1 = \beta_2 = 0$. The OLS estimator delivers an elasticity of substitution equal to 1.30, which leads to the conclusion that physical inputs and labor are gross substitutes. By contrast, the GMM estimate equals 0.75, implying that they are gross complements. These estimates are in line with existing literature (Doraszelski and Jaumandreu, 2018; Raval, 2019; Humlum, 2021; Oberfield and Raval, 2021). Even if estimating the elasticity of substitution between physical inputs and labor is not the primary goal of my analysis, replicating the findings of previous studies increases the estimator credibility.

In Column (3), I estimate equation (9) allowing only past productivity and robot adoption choices to impact current labor-augmenting productivity (i.e., setting $\beta_2 = 0$). Column (3) delivers two main insights. First, it confirms that physical inputs and labor are gross complements at the firm-level. Second, it shows that robot adopters have lower labor-augmenting productivity and a 40% higher physical inputs-to-labor ratio than non-adopters, on average.[51] Finally, Column (4) reports the estimates from the full model. Conditional on input prices and robot adoption, the estimates reveal that past ownership structure does not produce a direct significant effect on current labor-

[51] The estimated coefficient of β_1 is -0.33, i.e., robot adoption reduces labor-augmenting productivity. However, because B_{ft} enters with negative sign in equation (8), the coefficient in Table 5 is positive. Finally, since the left-hand side of equation (8) is in logarithm, the average effect is $(\exp(0.33) - 1) = 40\%$. The same argument applies to the estimated coefficient of β_2.

augmenting productivity.[52] Overall, the estimates suggest that it is robot adoption, rather than foreign ownership per se, to tilt production towards physical inputs.

Table 5: Labor-Augmenting Productivity

Dependent Variable:	Log(Physical Inputs/Employees)$_{ft}$			
	(1)	(2)	(3)	(4)
Log(Wage/Int. Rate)$_{ft}$	1.3***	0.75***	0.65***	0.67***
	(0.04)	(0.05)	(0.05)	(0.06)
Robot$_{ft-1}$			0.33***	0.34***
			(0.05)	(0.05)
Foreign-Owned$_{ft-1}$				-0.13
				(0.13)
Observations	5,697	5,697	5,697	5,697
Estimator	OLS	GMM	GMM	GMM

Note: The unit of observation is a firm-time interval pair. A time interval is a three-year time window. Log(Physical Inputs/Employees)$_{ft}$ is the log of the ratio of the physical input expenditure and number of employees. Log(Wage/Int. Rate)$_{ft}$ is the log of the ratio of the gross workers' wages and capital interest rate. Robot$_{ft}$ is a binary variable equal to 1 if firm f employs a robot in the current time interval and 0 otherwise. Foreign-Owned$_{ft}$ is a binary variable equal to 1 if firm f is foreign-owned in the current time interval and 0 otherwise. Standard errors in parenthesis. Significance levels: *** 0.01, ** 0.05, * 0.1.

Because the model is just-identified, I cannot test if the exclusion restrictions jointly hold. However, following the method proposed by Andrews, Gentzkow and Shapiro (2017), Figure D.1 shows that the estimates in Column (4) are insensitive to local deviations in the moment condition involving the excluded instrument (i.e., $\mathbb{E}\left[\log(L_{ft-1})u_{ft}\right] = 0$). This fact increases the confidence that past employment level are a valid instrument for current relative factor prices and that the parameters of interest are identified.

Next, I estimate TFP from quation (12). Table 6 shows the estimates I obtain by adding one regressor at a time.[53] Column (1) shows that TFP is strongly persistent over time, with the coefficient associated with the auto-regressive term being equal to 0.97. Column (2) shows that, conditional on past productivity, robot adopters are about 32% more productive than non-adopting firms, on average. Finally, Column (3) shows that, conditional on past productivity and robot adoption, foreign-owned firms are

[52] However, because it spurs robot adoption (see Table 2), foreign ownership does produce an indirect effect on within-firm input factors' reallocation.

[53] In each column, I also include the current value of the log of labor-augmenting productivity to purge the indirect effect that robot adoption and foreign ownership produce on TFP through it. The unconditional correlation between Log TFP and Log labor-augmenting productivity is about 0.95. In an unreported specification, I also compute bootstrap standard errors to account for the fact that TFP is estimated. The significance levels in Table 6 are unaltered.

about 43% more productive than domestic ones.[54] Hence, unlike for labor-augmenting productivity, both robot adoption and foreign ownership contribute to TFP growth.

Table 6: Total Factor Productivity

Dependent Variable:		Log(TFP)_{ft}	
	(1)	(2)	(3)
Log(TFP)_{ft-1}	0.97***	0.96***	0.96***
	(0.002)	(0.002)	(0.002)
Robot_{ft-1}		0.32***	0.29***
		(0.05)	(0.05)
$\text{Foreign-Owned}_{ft-1}$			0.43***
			(0.15)
Observations	3,442	3,442	3,442
Estimator	OLS	OLS	OLS

Note: The unit of observation is a firm-time interval pair. A time interval is a three-year time window. Log(TFP)_{ft} is the log of total factor productivity. Robot_{ft} is a binary variable equal to 1 if firm f employs a robot in the current time interval and 0 otherwise. $\text{Foreign-Owned}_{ft}$ is a binary variable equal to 1 if firm f is foreign-owned in the current time interval and 0 otherwise. Standard errors in parenthesis. Significance levels: *** 0.01, ** 0.05, * 0.1.

6.3 Counterfactuals

I use equations (10) and (12) to infer the relative importance of foreign ownership and robot adoption to explain changes in industry-level TFP and the labor share in the Spanish manufacturing industry over the sample period. Simulating these equations forward while shutting down the contribution of robot adoption or foreign ownership on productivity allows me to reconstruct counterfactual firm-level productivity paths, which I then aggregate up at the industry level.

I consider two different counterfactual scenarios. In the first one, I shut down the effect of foreign ownership on productivity (i.e., I set $\zeta_3 = 0$ in equation (12)). To account for the effect that foreign ownership exerts on the probability of robot adoption, I also discount ζ_2 in equation (12) by 10%, which is the foreign ownership robot adoption premium I estimate in Table 2. In the second one, I shut down both the effect of foreign ownership and robot adoption (i.e., I set $\beta_1 = 0$ in equation (10) and $\zeta_2 = \zeta_3 = 0$ in equation (12)). Since it is insignificant in Table 5, I set $\beta_2 = 0$ in all scenarios.

[54]This result is consistent with literature showing that foreign-owned firms are better managed than domestic ones (Bloom et al., 2012).

In each scenario, I compute counterfactual outcomes in two steps. First, starting from their observed productivity levels in the first sample period, I simulate counterfactual firm-level TFP and labor share paths by rolling forward equations (10) and (12).[55] Second, I aggregate the results at the industry level using the observed firms' employment shares each year, which I keep constant across scenarios. To avoid dealing with sample attrition due to entry and exit, I focus on the sub-sample of active firms between 1993 and 2014.[56] I provide further implementation details in Appendix D.2.

Figure 2 shows the results. For benchmark purposes, the first scenario (Baseline) shows the observed industry-level TFP and labor share trajectories. The results indicate that TFP grew by about 0.60% and labor share decreased by about 18.07% over the sample period. These figures are qualitatively similar to Doraszelski and Jaumandreu (2018). The second scenario (No MNEs) shows the counterfactual outcomes that I obtain when shutting down the effect of foreign ownership. Absent MNEs, the total TFP change would have been equal to −0.25%, i.e., 0.85 percentage points lower than the baseline. By contrast, the labor share would have decreased by 16.60%, i.e., 1.47 percentage points less than under the baseline scenario.

The third scenario (Neither MNEs nor Robots) shows the counterfactual outcomes that I obtain when shutting down the foreign ownership and robot adoption effects on productivity simultaneously. In the absence of MNEs and robots, the total TFP change would have been −0.50%, i.e., about 1.10 percentage point lower than the baseline. By contrast, the labor share would have increased by 1.20%, i.e., about 19.27 percentage points more than the baseline. Hence, multinational activity explain ($0.85/1.10 \approx$) 77% of the total TFP drop between the baseline and a scenario without MNEs and robots. By contrast, it explains about ($1.47/19.27 \approx$) 7% of the total labor share increase across counterfactual scenarios.

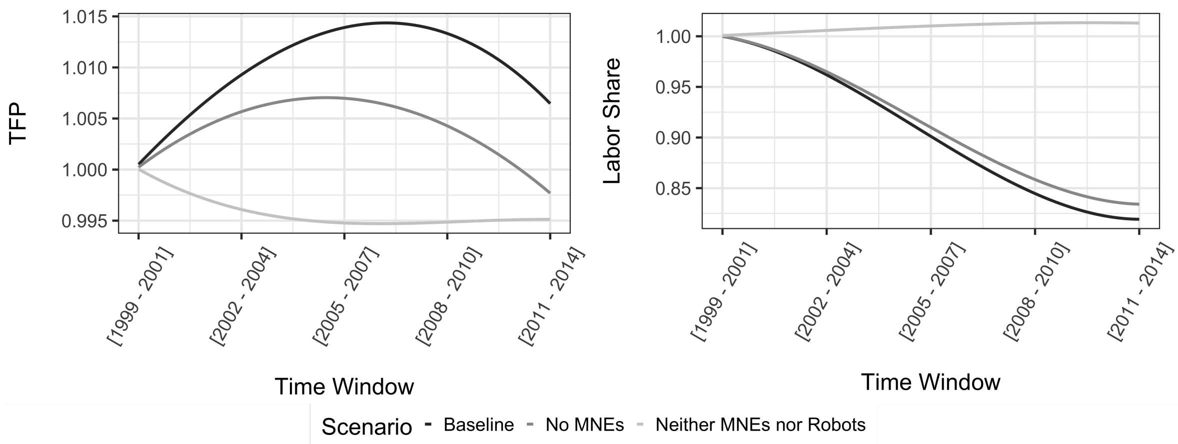
Overall, the counterfactual exercise delivers two insights. First, multinational activity produces substantial TFP gains but puts downward pressure on the labor share by boosting robot adoption. However, the first effect is one order of magnitude larger than the second one.[57] Although the model is silent about total welfare, the results provide new evidence about the efficiency versus equity trade-off that policymakers face when

[55]Firm-level TFP comes from equation (11). The labor (cost) share is $w_{ft}L_{ft}/(w_{ft}L_{ft} + r_{jt}M_{ft})$.

[56]There are 161 firms in this sub-sample. 5 become foreign-owned, whereas 70 employ a robot at least once. By contrast, there are 3611 firms in the baseline sample. 123 become foreign-owned, whereas 874 employ a robot at least once. While the share of foreign-owned firms is about 3% in both samples, the share of robot adopters in the sub-sample (about 43%) is about twice as large than in the baseline sample (about 24%). Therefore, the results I obtain when shutting down the robot adoption productivity effect should be understood as an upper bound of the effect in the full sample.

[57]This number mirrors the fact that foreign ownership produces both a direct and an indirect effect (via robot adoption) on TFP (Table 6) but only an indirect one on labor-augmenting productivity (Tables 2 and 5).

Figure 2: Counterfactual Scenarios



Note: The Figure shows the changes of industry-level TFP and labor share over the sample period under three different scenarios. The first scenario reports total growth rates under the baseline scenario. In this scenario, the total TFP growth rate is 0.60% and the total labor share growth rate is -18.07%. The second scenario is a counterfactual without MNEs. In this case, I also discount the robot adoption productivity effect of foreign-owned firms by 10%, which is the foreign ownership robot adoption premium I estimate in Table 2. In this scenario, the total TFP growth rate is -0.25% and the total labor share growth rate is -16.60%. Finally, the third scenario is a counterfactual without MNEs and robots. In this scenario, the total TFP growth rate is -0.50% and the total labor share growth rate is 1.20%. See Appendix D.2 for the implementation details.

attracting foreign investment.

Second, the results offer a new perspective on the observed decline in the manufacturing labor share in many advanced economies. In a recent survey of the literature, Grossman and Oberfield (forthcoming) mention globalization and automation as two leading explanations for this phenomenon. Figure 2 reinforces and extends their argument. Rather than being separate causes, the joint interaction of MNEs' activities (globalization) and robot adoption (technological change) contributes the observed decline. Notwithstanding, robots are disproportionally more important than multinationals in driving this process.

7 Conclusion

In this paper, I show that multinational enterprises spur the adoption of industrial robots. This result is new in the literature and has relevant policy implications because robots may increase productivity but also replace workers in routine tasks.

I exploit new cross-country industry-level data and detailed firm-level data for Spanish manufacturing. I use the first data source to document a positive and robust correlation between multinational production and robot adoption. I use the second data source to study if firms switching from domestic to foreign ownership become more likely to employ robots. Combining a difference-in-differences approach with a propensity score reweighing estimator, I find that acquired firms are about 10% more likely to employ robots. In terms of mechanism, I provide evidence that foreign parents grant increased market access to their affiliates. In turn, the possibility of expanding into global markets creates incentives to scale-up production, and robot adoption is one way to accomplish this result.

Whereas switching to foreign ownership generates significant gains for their affiliates (reflected, e.g., in an increase in sales and employment), I also find evidence that the labor share falls within acquired firms, indicating that switching to foreign ownership shifts income away from labor. These insights inform a dynamic partial equilibrium firm investment model, which I use to further investigate the productivity and distributional effects of foreign ownership and robot adoption.

The model estimates deliver two main insights. First, robot adoption and foreign ownership increase firm-level total factor productivity. Second, it is robot adoption, rather being foreign-owned per se, to reallocate income away from labor. A counterfactual economy without robots and multinationals would have lower productivity but a higher labor share. Overall, these results provide new evidence on the efficiency versus equity trade-off that policymakers face when attracting foreign investment.

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Appendices

Appendix A Firm-Level Data Description

A.1 Tables

Table A.1: Summary Statistics by Ownership Type

	Domestic		Foreign	
	Mean	SD	Mean	SD
Panel A: Automation Technology				
Robot	0.17	0.37	0.36	0.48
Numerically Controlled Machines	0.39	0.49	0.55	0.50
CAD Manufacturing	0.28	0.45	0.44	0.50
Flexible Systems	0.19	0.40	0.39	0.49
Panel B: Type of Manufacturing				
Batch Manufacturing	0.55	0.50	0.24	0.43
Mass Manufacturing	0.35	0.48	0.61	0.49
Continuous Manufacturing	0.08	0.26	0.14	0.34
Mixed Manufacturing	0.02	0.14	0.02	0.13
Panel C: Technological Effort				
Effort to Assimilate Foreign Technology	0.06	0.24	0.24	0.43
Import of Foreign Technology (Hundred Euros)	0.05	1.17	2.41	14.45
Panel D: Innovation and Research and Development				
Innovation Plan	0.09	0.29	0.39	0.49
Total RD Expenses (Million Euros)	0.08	1.43	1.41	3.40
Internal RD (Million Euros)	0.05	0.91	1.02	2.55
Panel E: Other Characteristics				
Exporter	0.47	0.50	0.86	0.35
Export Via Parental Network	0.00	0.00	0.29	0.45
Exports (Million Euros)	2.50	17.02	41.32	122.29
No. of Export Markets	0.46	0.84	1.20	1.09
Gross Wage per Employee (Thousand Euros)	24.78	9.30	35.95	12.91
Employees	64.86	202.19	594.33	1283.18
Share of Graduates	0.05	0.09	0.08	0.08
Investment (Million Euros)	0.31	1.44	4.80	23.59
Physical Inputs (Million Euros)	5.12	20.86	115.64	428.56
Sales (Million Euros)	10.06	46.91	141.42	421.64
Labor Productivity (Million Euros)	0.12	0.17	0.18	0.15

Note: The Table shows the average (Mean) and standard deviation (SD) of the ESEE variables in my sample. The sub-sample of domestic firms includes those that stay under domestic ownership during their life span. The sub-sample of foreign-owned firms includes those that switch from domestic to foreign ownership at most once during their life span. Overall, foreign-owned firms outperform domestic-owned ones in all dimension. See Table A.2 for the variables' description.

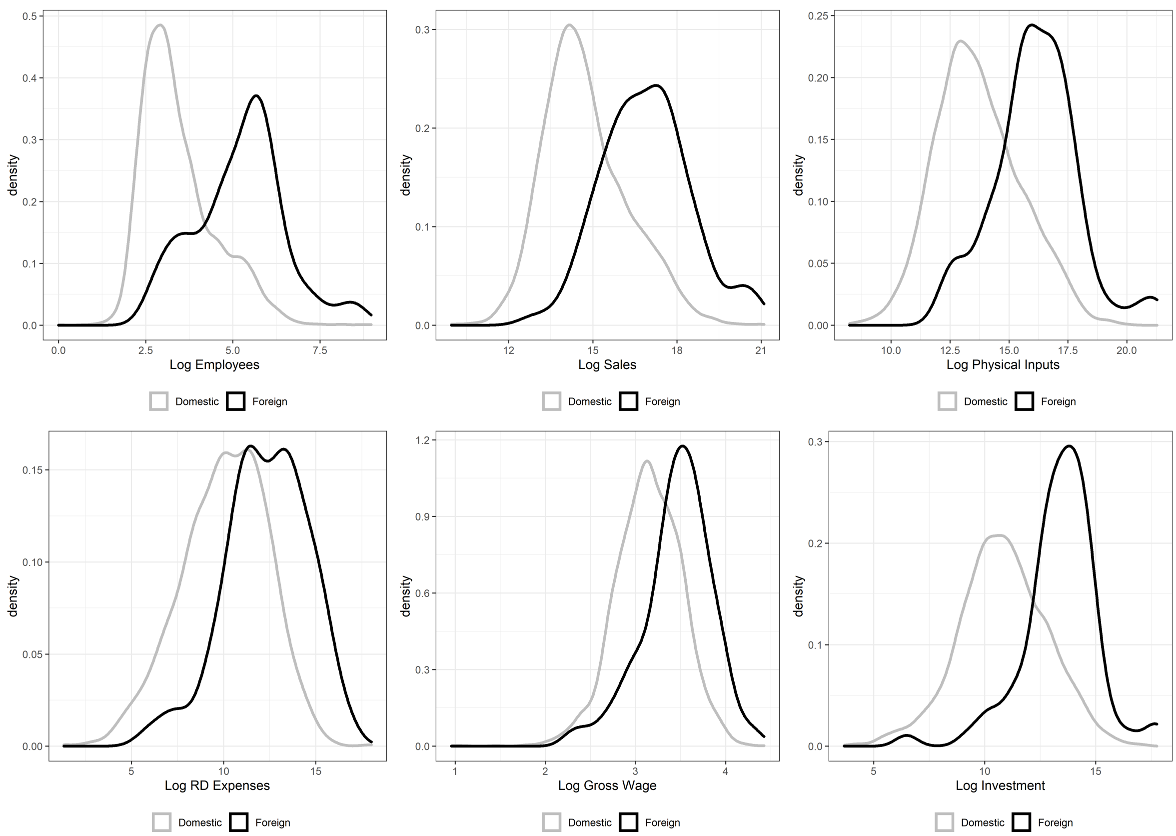
Table A.2: Variables' Description

Variable	*Range/Unit*	*Frequency*	*Description*
Robot Adoption	[0, 1]	Q	= 1 if firm employs robot
Numerically Controlled Machines	[0, 1]	Q	= 1 if firm employs numerically controlled machines
CAD Manufacturing	[0, 1]	Q	= 1 if firm employs CAD manufacturing
Flexible Systems	[0, 1]	Q	= 1 if firm employs flex. systems
Batch Manufacturing	[0, 1]	Q	= 1 if firm performs batch manuf.
Mass Manufacturing	[0, 1]	Q	= 1 if firm performs mass manuf.
Continuous Manufacturing	[0, 1]	Q	= 1 if firm performs continuous manuf.
Mixed Manufacturing	[0, 1]	Q	= 1 if firm performs mixed manuf.
Import of Foreign Technology	Euros	Q	Payments for licenses and technical aid from abroad
Total RD Expenses	Euros	A	Total research and development expenses
Internal RD	Euros	A	Internal research and development expenses
Exporter	[0, 1]	A	= 1 If firm exports abroad
Export Via Parental Network	[0, 1]	Q	= 1 If firm exports via its foreign parent
Exports	Euros	A	Value of exports
No. of Export Markets	$[0, \infty)$	A	Number of foreign markets served
Gross Wage per Employee	Euros	A	Labor costs divided by number of employees
Employees	$[0, \infty)$	A	Total number of employees
Investment	Euros	A	Value of investment in tangible assets
Physical Inputs	Euros	A	Value ot tangible fixed assets (no buildings and land)
Sales	Euros	A	Value of sales
Labor Productivity	Euros	A	Sales per employee
Prince Index	[-100, 100]	A	Change of the sale prices between two years
Foreign-Owned	Euros	A	= 1 If firm is foreign-owned
Owns Equity Shares Abroad	Euros	A (post 2000)	= 1 If firms controls foreign companies
Activity	Number	A	2-digit manufacturing industry
Change Nature	Factor	A	Reports if firm changed its nature

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

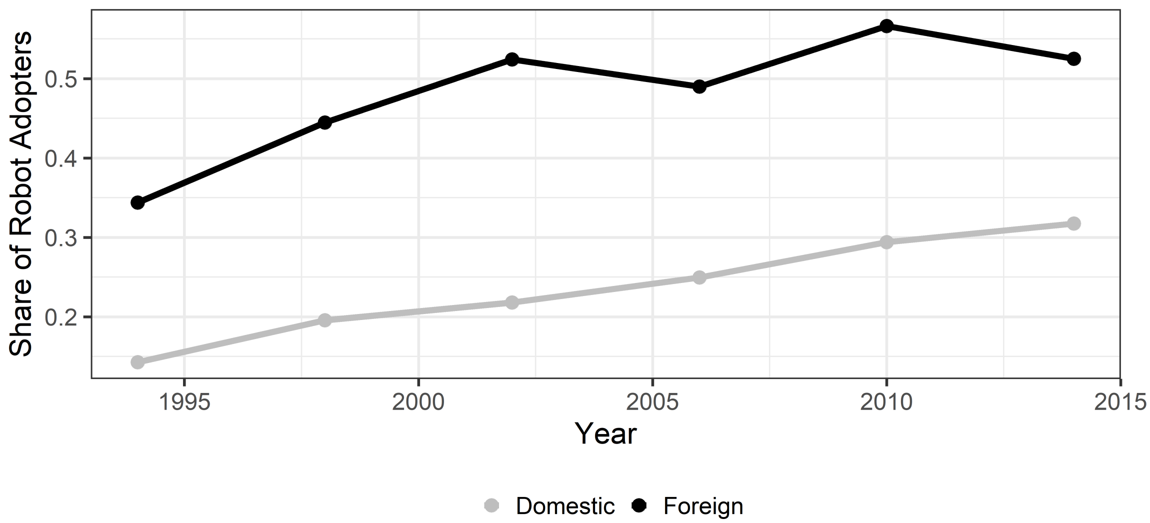
A.2 Figures

Figure A.1: Covariates' Density Plots by Ownership



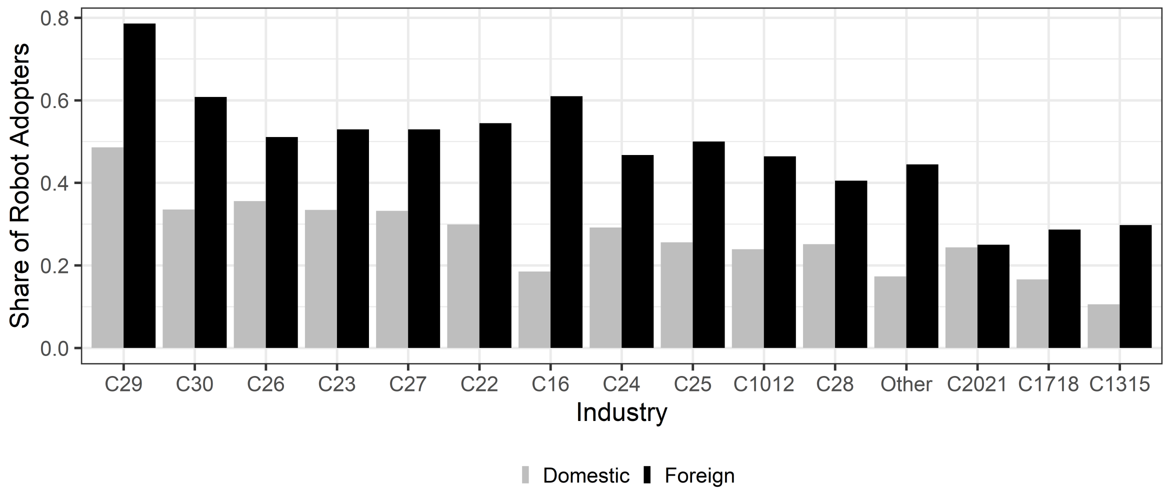
Note: The Figure shows the empirical probability density function (pdf) of the log of employees, sales, physical inputs, R&D expenses, wages, and investment by ownership type. I estimate the empirical pdf functions for domestic-owned firms based on their lifetime characteristics. I estimate it only for the years before the acquisition date for foreign-owned ones. Overall, foreign-owned firms outperform domestic-owned ones along all dimensions already before the acquisition.

Figure A.2: Share of Robot Adopters by Ownership and Year



Note: The Figure shows the share of robot adopters among foreign-owned and domestic-owned firms between 1994 and 2014. Although the share of robot adopters has steadily grown in both sub-samples, the proportion of robot adopting firms among foreign-owned firms is about twice as large than among domestic-owned ones in any given year.

Figure A.3: Share of Robot Adopters by Ownership and Industry



Note: The Figure shows the share of robot adopters among foreign-owned and domestic-owned firms across industries. The shares are averages between 1994 and 2014. Overall, the share of robot adopting firms among foreign-owned firms is systematically larger than among domestic-owned ones across industries. The automotive industry (C29) witnesses the highest adoption rates.

Appendix B Industry-Level Data Description

B.1 Sample Construction and Data Cleaning

Using the IFR data requires addressing two issues. 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. This data feature contrasts with standard notions of physical capital accumulation. For this reason, I follow Graetz and Michaels (2018) and employ a permanent inventory method to compute the stock of robots in each country-industry-year cell. The procedure consists of two steps. In the first step, I take as initial value the first available data about the number of deployed robots at the country-industry level. In the second one, I calculate subsequent values using the information about new installations and assuming a yearly depreciation rate of 10%.

Second, about 20% of the stock cannot be allocated to any ISIC review 4 industry in some countries. I follow Graetz and Michaels (2018) and allocate these robots proportionally to each sector based on their share of deployed robots across all sample years. I present my baseline results using the adjusted data. However, the my findings in Section 4 hold regardless of this choice.

Besides, merging data from AMNE, IFR, and WIOD SEA also requires tackling two challenges. First, one has to homogenize industry definitions. AMNE and WIOD follow indeed the ISIC review 4 classification, whereas the IFR has its own system. However, since the IFR closely follows the ISIC review 4, it is feasible to match industries without ambiguity based on the industry description.

Second, the three datasets use a different industry aggregation level. Because the AMNE data have the most aggregate industry classification, I group industries in the IFR and WIOD SEA to match the AMNE classification. The final dataset contains the following 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 n.e.c.), "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).

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

$$X_{pyp}(t) = X(t) \times \frac{D(t)}{D(t-1)}.$$

$X_{pyp}(t)$ is the variable of interest in year t in previous-year prices, $X(t)$ is the nominal level of the variable of interest and $D(t)/D(t-1)$ is the ratio of the output deflator between two consecutive periods. Finally, I convert them into US dollars using the nominal exchange rate provided by WIOD SEA.

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

B.2 Additional Results

Table B.1: Summary Statistics

Variable	N	Mean	St. Dev.	Min	Q25	Median	Q75	Max
Log Robot Stock	6563	2.95	3.49	-8.21	0.95	3.12	5.29	12.75
Log MNEs' Production	6563	7.64	2.02	-0.05	6.39	7.80	9.02	12.78
Log Employees	6563	4.61	2.14	-3.22	3.18	4.47	5.91	12.60
Log Capital Stock	6563	9.27	2.07	1.11	8.05	9.28	10.74	14.63
Log Wages	6563	7.94	1.93	0.85	6.76	7.89	9.27	13.73
Log Interest Rate	6563	7.58	2.03	-1.46	6.39	7.62	8.87	12.79

Note: The Table shows summary statistics for the sample I construct in section 3.1.

B.3 Tables

Table B.2: Industry-Level Correlations (Robustness)

Dependent Variable:	Log(Robots/Thousand Employees)$_{cit}$	
	(1)	(2)
Log(Multinational Production)$_{cit}$	0.22***	0.26***
	(0.03)	(0.03)
Log(Capital Stock/Thousand Employees)$_{cit-1}$	0.15***	0.13***
	(0.04)	(0.04)
Log(Interest Rate/Wages)$_{cit-1}$	-0.09*	-0.08*
	(0.04)	(0.04)
Industry-Year FE	Yes	Yes
Country-Year FE	Yes	Yes
Sample	No C29	No Top 5
Observations	5,429	4,886
Estimator	OLS	OLS

Note: The unit of observation is a country-industry-year tuple. Log(Robots/Thousand Employees)$_{cit}$ is the log of the number of robots per thousand employees in country c's industry i in year t. Log(Multinational Production)$_{cit}$ is the log of gross output produced by foreign-owned firms in country c's industry i in year t. Log(Capital Stock/Thousand Employees)$_{cit}$ is the capital stock per thousand employees in country c's industry i in year t. Log(Interest Rate/Wages)$_{cit}$ is the ratio between the capital interest rate and gross wages in country c's industry i in year t. Heteroscedasticity-robust standard errors in parenthesis. Significance levels: *** 0.01, ** 0.05, * 0.1.

B.3.1 Specification Robustness

To ensure that the baseline results do not merely pick-up pre-sample trends, I estimate the following long-difference equation:

$$\Delta R_{ci} = \beta \Delta MP_{ci} + \alpha_c + \alpha_i + \varepsilon_{ci} \tag{13}$$

ΔR_{ci} is the country-industry level change in the stock of robots. I measure the change both between 2005 and 2014, and 1993 and 2004. I use the first version as baseline and the second one as placebo. ΔMP_{ci} is the country-industry level change in multinational production between 2004 and 2015. Finally, α_c and α_i are country-level, respectively industry-level, fixed effects to account for the fact that different countries and industries have experiences heterogeneous trends robot adoption trends.

The main parameter of interest is β. I standardize all variables to have zero mean in the sample before performing the estimation. Therefore, it measures the effect of increasing the change in multinational production by one unit on the change in the robot stock at the country-industry level. Since I compute ΔMP_{ci} between 2005 and 2014, I expect β to be positive and significant when using ΔR_{ci} between 2005 and 2014 as an outcome, and insignificant when using the change between 1994 and 2004.

Table B.3 shows the results. As expected, the total change in multinational production positively correlates with the total change in the number of deployed robot during the sample period, but not before.

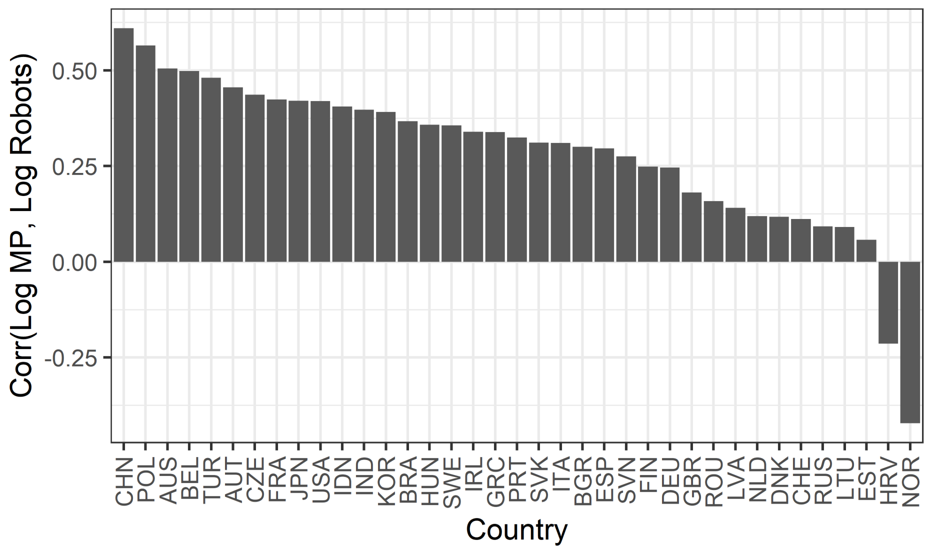
Table B.3: Cross-Country Industry-Level Correlations (Long-Difference)

Dependent Variables:	ΔRobots$_{ci}$ (2005-2014) (1)	ΔRobots$_{ci}$ (1994-2004) (2)
ΔMultinational Production$_{ci}$	0.29*	0.03
	(0.17)	(0.04)
Country FE	Yes	Yes
Industry FE	Yes	Yes
Observations	740	740
Estimator	OLS	OLS

Note: ΔRobots$_{ci}$ (2005-2014) is the robot stock change in country c's industry i between 2005 and 2014. ΔRobots$_{ci}$ (1994-2005) is the robot stock change in country c's industry i between 1994 and 2004. ΔMultinational Production$_{ci}$ is the change in the gross output produced by affiliates of foreign firms in country c's industry i between 2005 and 2014. Heteroscedasticity-robust standard errors in parenthesis. Significance levels: *** 0.01, ** 0.05, * 0.1.

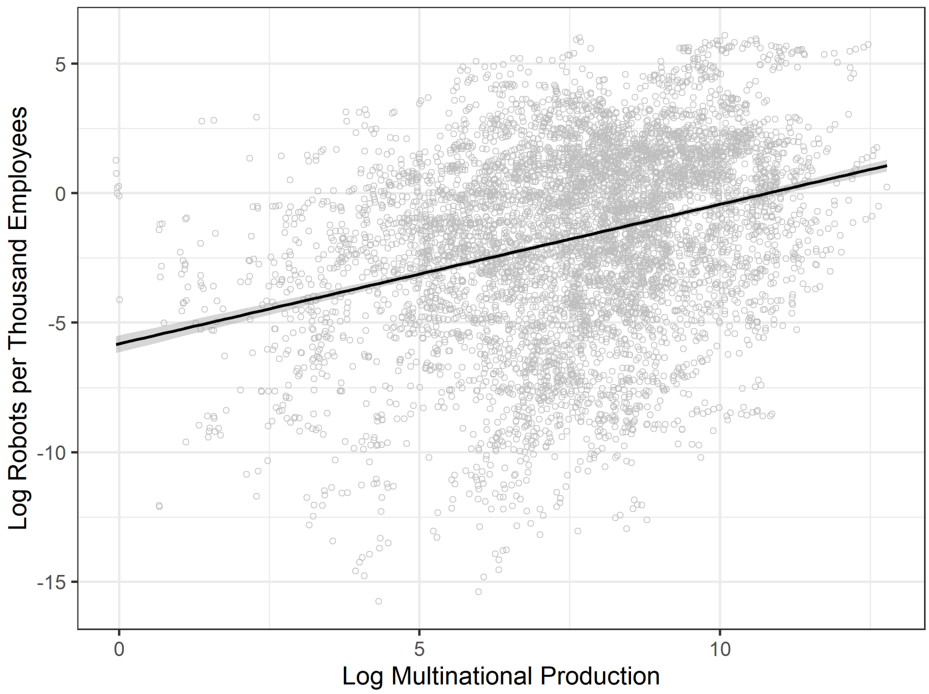
B.4 Figures

Figure B.1: Correlation between Multinational Production and Robots



Note: The Figure shows the correlation between the log of multinational production (MP) and the log of the number of deployed robots by country. I compute correlation across industries and years within countries. The correlation is positive in most countries. The sample average is about 30%, and it is strongest in China, where it peaks at about 60%.

Figure B.2: ROBOTS PER THOUSAND EMPLOYEES VS. MULTINATIONAL PRODUCTION



Note: The Figure shows the linear fit I obtain by regressing the log of the number of robots per thousand employees on the log of multinational production at the country-industry-year level. The estimated coefficient is about 0.5% and is significant at the 1% level.

Appendix C Additional Firm-Level Results

C.1 Tables

Table C.1: Propensity Score (Probit) Regressions

Dependent Variable:					Foreign-Owned$_{ft}$					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Interecept	-2.6***	-2.6***	-7.4***	-5.7***	-6.0***	-6.1***	-6.1***	-5.7***	-5.3***	-5.4***
	(0.04)	(0.04)	(0.36)	(0.47)	(0.49)	(0.54)	(0.53)	(0.55)	(0.66)	(0.66)
Sales Growth Rate$_{ft}$		0.25***	0.44***	0.30***	0.26***	0.27***	0.26***	0.25***	0.25***	0.25***
		(0.07)	(0.08)	(0.08)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
Log(Sales)$_{ft-1}$			0.30***	0.13***	0.07	0.08	0.07	0.07	0.03	0.03
			(0.02)	(0.04)	(0.06)	(0.06)	(0.07)	(0.07)	(0.08)	(0.08)
Log(Employees)$_{ft-1}$				0.25***	0.29***	0.29***	0.28***	0.24***	0.25***	0.25***
				(0.06)	(0.07)	(0.07)	(0.07)	(0.08)	(0.08)	(0.08)
Log(Wages)$_{ft-1}$					0.32**	0.32**	0.31*	0.23	0.25	0.27
					(0.16)	(0.16)	(0.17)	(0.17)	(0.17)	(0.18)
Log(Investment)$_{ft-1}$						-0.005	-0.005	-0.008	-0.009	-0.009
						(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Log(Physical Inputs)$_{ft-1}$							0.01	0.01	0.008	0.01
							(0.05)	(0.05)	(0.05)	(0.05)
Log(R&D Expenses)$_{ft-1}$								0.03***	0.02***	0.02***
								(0.007)	(0.008)	(0.008)
Log(Exports)$_{ft-1}$									0.02*	0.02**
									(0.01)	(0.01)
No. Export Countries$_{ft-1}$										-0.05
										(0.04)
Observations	18,896	18,896	18,896	18,896	18,896	18,896	18,896	18,896	18,896	18,896
Estimator	Probit	Probit	Probit	Probit	Probit	Probit	Probit	Probit	Probit	Probit

Note: The unit of observation is a firm. Foreign-Owned$_{ft}$ is a binary variable equal to 1 if firm f becomes foreign-owned at some point during its life and 0 otherwise. Sales Growth Rate$_{ft}$ is the sales' growth rate between the acquisition year and the one before. Log(Sales)$_{ft-1}$ is the lag of (the log of) firm sales. Log(Employees)$_{ft-1}$ is the lag of (the log of) the number of employees. Log(Wages)$_{ft-1}$ is the lag of (the log of) firm wages. Log(Investment)$_{ft-1}$ is the lag of (the log of) firm investment. Log(Physical Inputs)$_{ft-1}$ is the lag of (the log of) firm physical inputs. Log(R&D Expenses)$_{ft-1}$ is the lag of (the log of) R&D expenses. Log(Export)$_{ft-1}$ is the lag of (the log of) export sales. Log(Export Countries)$_{ft-1}$ is the lag of (the log of) the number of export countries served by the firm. Heteroscedasticity-robust standard errors in parenthesis. Significance levels: *** 0.01, ** 0.05, * 0.1.

Table C.2: Covariates' Balance Before and After Reweighing

Sample	Employees	Sales	Export Value	No. Export Markets	Wages	Physical Inputs	Investment	R&D Expenses	Sales' Growth
Unweighed	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Reweighed	0.82	1.00	0.74	0.73	0.94	0.97	0.74	0.96	0.48

Note: Each row shows the p-value associated with the null hypothesis that acquired and non-acquired firms have the same average characteristics along the dimensions reported in columns. The first row shows the p-value computed in the unmatched (baseline) sample. The second row shows the p-value computed in the matched sample, i.e., after reweighing acquired firms by $1/\widehat{p}$ and non-acquired ones by $1/(1-\widehat{p})$, being $\widehat{p}$ the estimated probability of becoming foreign-owned. Whereas I always reject the null hypothesis that the two groups have different average characteristics, I never reject it post-matching.

Table C.3: Industry-Level Heterogeneity

Dependent Variable:	Robot$_{ft}$			
	(1)	(2)	(3)	(4)
Foreign-Owned$_{ft}$ × Diffusion Tercile = 1	0.27***			
	(0.09)			
Foreign-Owned$_{ft}$ × Diffusion Tercile = 2	0.13**			
	(0.06)			
Foreign-Owned$_{ft}$ × Diffusion Tercile = 3	-0.02			
	(0.06)			
Foreign-Owned$_{ft}$		0.13*	0.15**	-0.06
		(0.08)	(0.06)	(0.06)
Firm FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Sample	Full	Diffusion Tercile = 1	Diffusion Tercile = 2	Diffusion Tercile = 3
Observations	18,520	1,592	11,775	5,153
Estimator	IPRW	IPRW	IPRW	IPRW

Note: The unit of observation is a firm-year pair. Robot$_{ft}$ is a binary variable equal to 1 if firm f employs a robot in year t and 0 otherwise. Foreign-Owned$_{ft}$ is a binary variable equal to 1 if firm f is foreign-owned in year t and 0 otherwise. I construct Robots' Diffusion Tercile as follows. First, I compute the number of industrial robots deployed in each Spanish manufacturing industry in 1993. Second, I group industries into terciles. The first tercile includes industries with the lowest robot adoption rate in 1993. In all columns, I reweigh acquired firms by $1/\widehat{p}$ and non-acquired ones by $1/(1-\widehat{p})$, being $\widehat{p}$ the estimated probability of becoming foreign-owned. Cluster standard errors by firm in parenthesis. Significance levels: *** 0.01, ** 0.05, * 0.1.

Table C.4: Firm-Level Mechanism Regressions (Step Two, Heterogeneity)

Dependent Variable:		Robot_{ft}	
	(1)	(2)	(3)
Exp. via Foreign Parent_{ft}	0.30***	0.45**	0.46**
	(0.08)	(0.19)	(0.19)
$\text{Foreign-Owned}_{ft-1}$	0.29**		0.28**
	(0.14)		(0.14)
Exp. via Foreign $\text{Parent}_{ft} \times \text{Foreign-Owned}_{ft-1} = 1$	-0.37*		-0.40**
	(0.20)		(0.20)
Exporter_{ft-1}		0.14**	0.13**
		(0.06)	(0.05)
Exp. via Foreign $\text{Parent}_{ft} \times \text{Exporter}_{ft-1} = 1$		-0.29	-0.12
		(0.20)	(0.19)
Firm FE	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes
Observations	2,895	2,895	2,895
Estimator	IPRW	IPRW	IPRW

Note: The unit of observation is a firm-year pair. Exp. via Foreign Parent_{ft} is binary variable equal to 1 if firm f exports via its foreign parental network at time t and 0 otherwise. $\text{Foreign-Owned}_{ft}$ is binary variable equal to 1 if firm f is foreign-owned at time t and 0 otherwise. Exporter_{ft} is binary variable equal to 1 if firm f exports at time t and 0 otherwise. In all columns, I reweigh acquired firms by $1/\widehat{p}$ and non-acquired ones by $1/(1-\widehat{p})$, being $\widehat{p}$ the estimated probability of becoming foreign-owned. Cluster standard errors by firm in parenthesis. Significance levels: *** 0.01, ** 0.05, * 0.1.

Table C.5: Covariates' Balance Before and After Reweighing (Domestic Acquisitions)

Sample	Employees	Sales	Wages	Physical Inputs	Exporter Status	Sales Growth	Employment Growth
Unweighed	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Reweighed	0.70	0.84	0.96	0.82	0.72	0.79	0.90

Note: Each row shows the p-value associated with the null hypothesis that acquired and non-acquired firms have the same average characteristics along the dimensions reported in columns. The first row shows the p-value computed in the unmatched (baseline) sample. The second row shows the p-value computed in the matched sample, i.e., after reweighing acquired firms by $1/\widehat{p}$ and non-acquired ones by $1/(1-\widehat{p})$, being $\widehat{p}$ the estimated probability of being acquired by a domestic firm. Whereas I always reject the null hypothesis that the two groups have different average characteristics, I never reject it post-matching.

Table C.6: Firm-Level Regressions (Domestic Acquisitions)

Dependent Variable:	Robot$_{ft}$			
	(1)	(2)	(3)	(4)
Merger$_{ft}$	0.13*	0.20***	0.19***	0.15
	(0.07)	(0.07)	(0.07)	(0.10)
Firm FE	No	Yes	Yes	Yes
Industry-Year FE	No	Yes	Yes	Yes
Selection Controls	No	No	Yes	No
Observations	16,264	16,264	15,377	16,264
Estimator	OLS	OLS	OLS	IPRW

Note: The unit of observation is a firm-year pair. Robot$_{ft}$ is a binary variable equal to 1 if firm f employs a robot in year t and 0 otherwise. Merger$_{ft}$ is a binary variable equal to 1 if firm f was acquired by another domestic firm in year $k \leq t$ and 0 otherwise. In the last column, I reweigh acquired firms by $1/\widehat{p}$ and non-acquired ones by $1/(1-\widehat{p})$, being $\widehat{p}$ the estimated probability of being acquired by a domestic firm. Cluster standard errors by firm in parenthesis. Significance levels: *** 0.01, ** 0.05, * 0.1.

Table C.7: Type of Production

Dependent Variables:	Batch Manuf.$_{ft}$	Mass Manuf.$_{ft}$	Mixed Manuf.$_{ft}$	Continuous Manuf.$_{ft}$
	(1)	(2)	(3)	(4)
Foreign-Owned$_{ft}$	-0.08**	0.02	-0.006	0.06*
	(0.04)	(0.05)	(0.009)	(0.04)
Firm FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Observations	18,214	18,214	18,214	18,214
Estimator	IPRW	IPRW	IPRW	IPRW

Note: The unit of observation is a firm-year pair. Batch Manuf.$_{ft}$ is a binary variable equal to 1 if firm f does batch manufacturing in year t and 0 otherwise. Mass Manuf.$_{ft}$ is a binary variable equal to 1 if firm f does mass manufacturing in year t and 0 otherwise. Mixed Manuf.$_{ft}$ is a binary variable equal to 1 if firm f does mixed manufacturing in year t and 0 otherwise. Continuous Manuf.$_{ft}$ is a binary variable equal to 1 if firm f does continuous manufacturing in year t and 0 otherwise. Foreign-Owned$_{ft}$ is a binary variable equal to 1 if firm f is foreign-owned in year t and 0 otherwise. In all columns, I reweigh acquired firms by $1/\widehat{p}$ and non-acquired ones by $1/(1-\widehat{p})$, being $\widehat{p}$ the estimated probability of becoming foreign-owned. Cluster standard errors by firm in parenthesis. Significance levels: *** 0.01, ** 0.05, * 0.1.

Table C.8: Other Automation-Type Non-Robotic Technology

Dependent Variables:	CAD Manufacturing$_{ft}$	Numerically Ctrl Machines$_{ft}$	Flex. Systems$_{ft}$	Any Non-Robotic Technology$_{ft}$
	(1)	(2)	(3)	(4)
Foreign-Owned$_{ft}$	0.05*	-0.06	0.02	0.003
	(0.03)	(0.04)	(0.03)	(0.04)
Firm FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Observations	18,467	18,467	18,463	18,467
Estimator	IPRW	IPRW	IPRW	IPRW

Note: The unit of observation is a firm-year pair. CAD Manufacturing$_{ft}$ is a binary variable equal to 1 if firm f used CAD manufacturing in year t and 0 otherwise. Numerically Ctrl Machines$_{ft}$ is a binary variable equal to 1 if firm f uses numerically controlled machines in year t and 0 otherwise. Flex. Systems$_{ft}$ is a binary variable equal to 1 if firm f employs flexible systems in year t and 0 otherwise. Any Non-Robotic Technology$_{ft}$ is a binary variable equal to 1 if firm f uses any of these three technologies and 0 otherwise. Foreign-Owned$_{ft}$ is a binary variable equal to 1 if firm f is foreign-owned in year t and 0 otherwise. In all columns, I reweigh acquired firms by $1/\widehat{p}$ and non-acquired ones by $1/(1-\widehat{p})$, being $\widehat{p}$ the estimated probability of becoming foreign-owned. Cluster standard errors by firm in parenthesis. Significance levels: *** 0.01, ** 0.05, * 0.1.

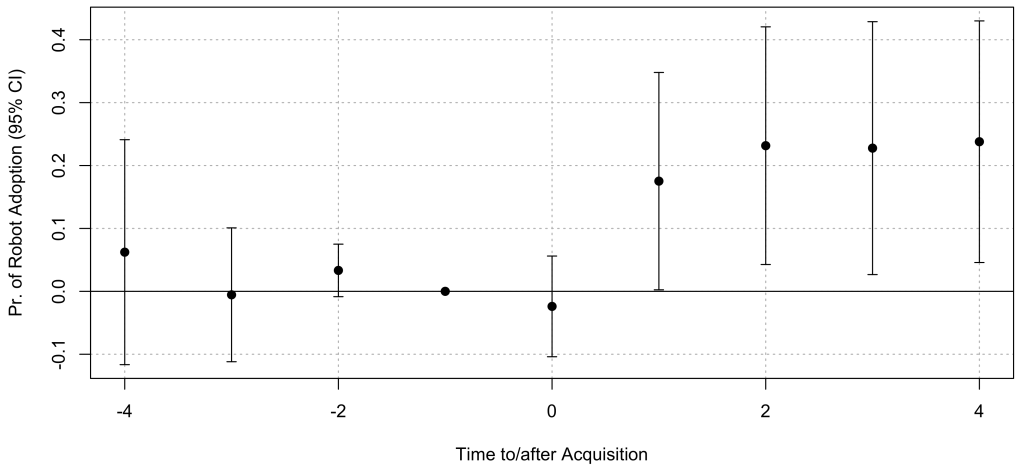
Table C.9: Within-Firm Gains and Distributional Outcomes

Dependent Variables:	Log(Sales)_{ft}	$\text{Log(Employees)}_{ft}$	Log(Wages)_{ft}	$\text{Log(Labor Productivity)}_{ft}$	$\text{Log(Sales/Wages)}_{ft}$
	(1)	(2)	(3)	(4)	(5)
$\text{Foreign-Owned}_{ft}$	0.32***	0.20***	0.09***	0.12***	0.23***
	(0.06)	(0.07)	(0.03)	(0.04)	(0.05)
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes
Observations	20,529	20,530	20,530	20,529	20,529
Estimator	IPRW	IPRW	IPRW	IPRW	IPRW

Note: The unit of observation is a firm-year pair. Log(Sales)_{ft} is the log of firm sales. $\text{Log(Employees)}_{ft}$ is the log of the number of employees. Log(Wages)_{ft} is the log of firm wages. $\text{Log(Labor Productivity)}_{ft}$ is the log of the ratio between firm sales and number of employees. $\text{Log(Sales/Wages)}_{ft}$ is the ratio between firm sales and wages. $\text{Foreign-Owned}_{ft}$ is a binary variable equal to 1 if firm f is foreign-owned in year t and 0 otherwise. In all columns, I reweigh acquired firms by $1/\widehat{p}$ and non-acquired ones by $1/(1-\widehat{p})$, being $\widehat{p}$ the estimated probability of becoming foreign-owned. Cluster standard errors by firm in parenthesis. Significance levels: *** 0.01, ** 0.05, * 0.1.

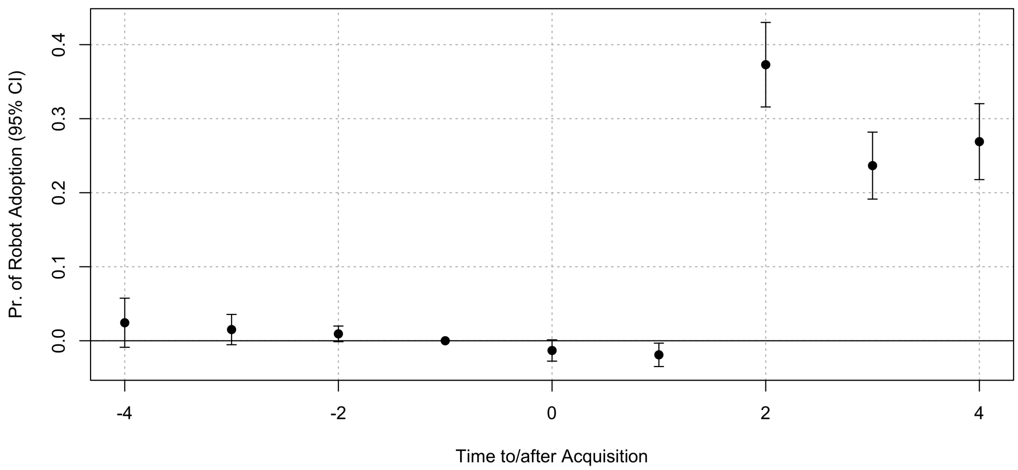
C.2 Figures

Figure C.1: Event-Study (Alternative Sample)



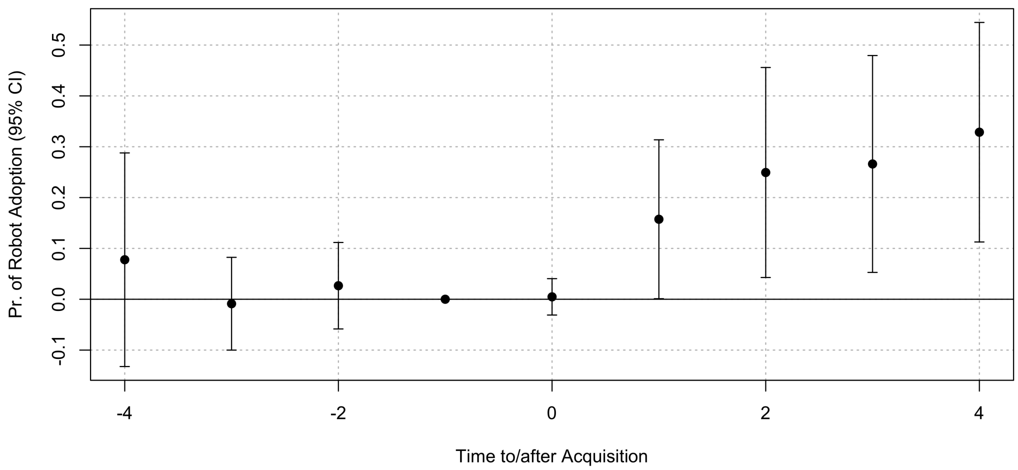
Note: The Figure plots the estimates (and the 95% confidence intervals around them) that I obtain from equation (2). The unit of observation is a firm-year pair, and I cluster standard errors by firm. The sample includes both acquired and always domestic firms. Starting from the first year after the acquisition date, affiliates become about 20% more likely to employ robots than in the year before the acquisition.

Figure C.2: Event-Study (Sun and Abraham, 2021)



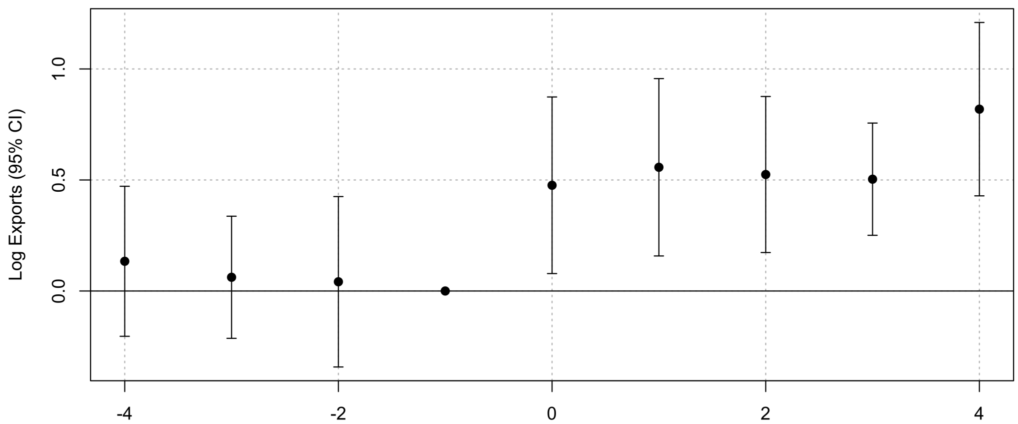
Note: The Figure plots the estimates (and the 95% confidence intervals around them) that I obtain from equation (2) using the method proposed by Sun and Abraham (2021). The unit of observation is a firm-year pair, and I cluster standard errors by firm. The sample includes both acquired and always domestic firms. Starting from second first year after the acquisition date, affiliates become about 25% more likely to employ robots than in the year before the acquisition. The estimates are not statistically different from those in Figure C.1

Figure C.3: Event-Study (Propensity Score Reweighing)



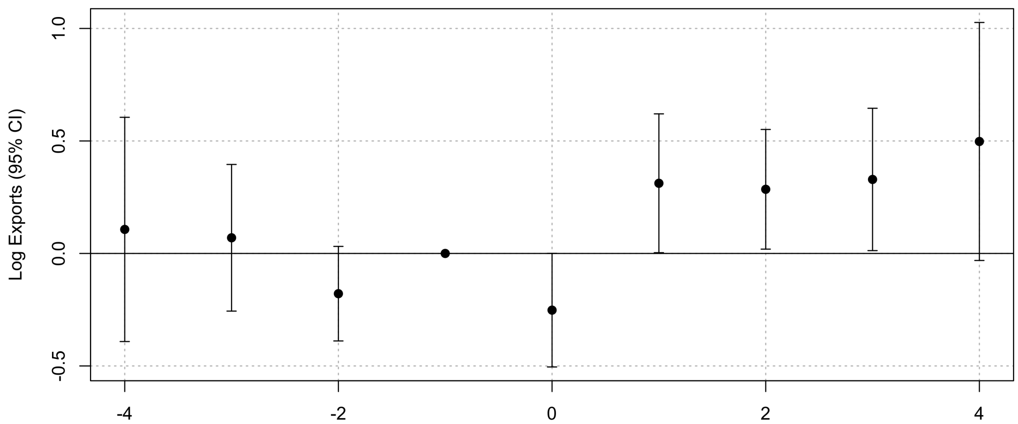
Note: The Figure plots the estimates (and the 95% confidence intervals around them) that I obtain from equation (2) after reweighing acquired firms by $1/\widehat{p}$ and non-acquired ones by $1/(1-\widehat{p})$, being $\widehat{p}$ the estimated probability of becoming foreign-owned. The unit of observation is a firm-year pair, and I cluster standard errors by firm. Starting from the first year after the acquisition date, affiliates become about 20% more likely to employ robots than comparable domestic-owned firms. Whereas it deliver similar post-acquisition estimates as in Figure C.1, the propensity reweighing procedure further assuages pre-acquisition trends.

Figure C.4: Event-Study (Export Via Foreign Parent)



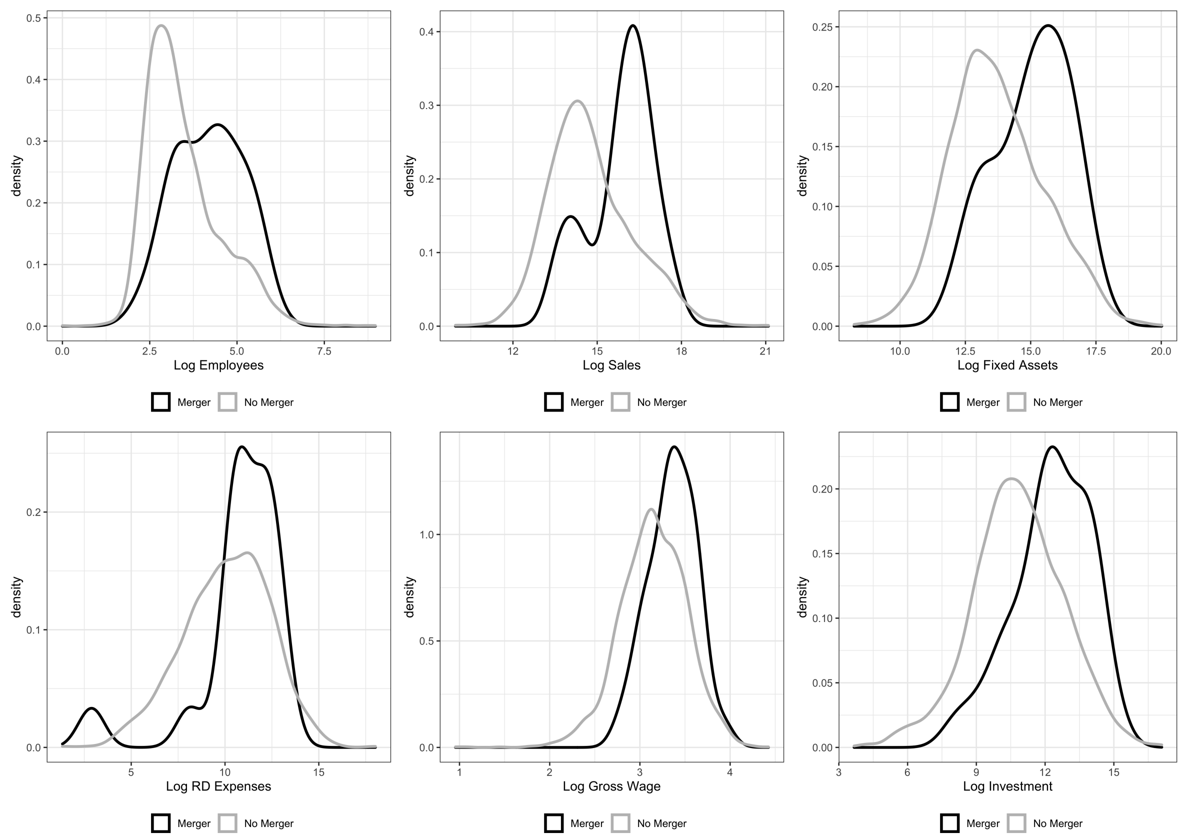
Note: The Figure plots the estimates (and the 95% confidence intervals around them) that I obtain by estimating equation (2) using the binary variable equal to 1 if a firm exports via her foreign parental network as outcome variable. I reweigh acquired firms by $1/\widehat{p}$ and non-acquired ones by $1/(1-\widehat{p})$, being $\widehat{p}$ the estimated probability of becoming foreign-owned. The unit of observation is a firm-year pair, and I cluster standard errors by firm. Starting from the first year after the acquisition date, affiliates are about 50% to export via their foreign parents than in the year before the acquisition.

Figure C.5: Event-Study (Exports Value)



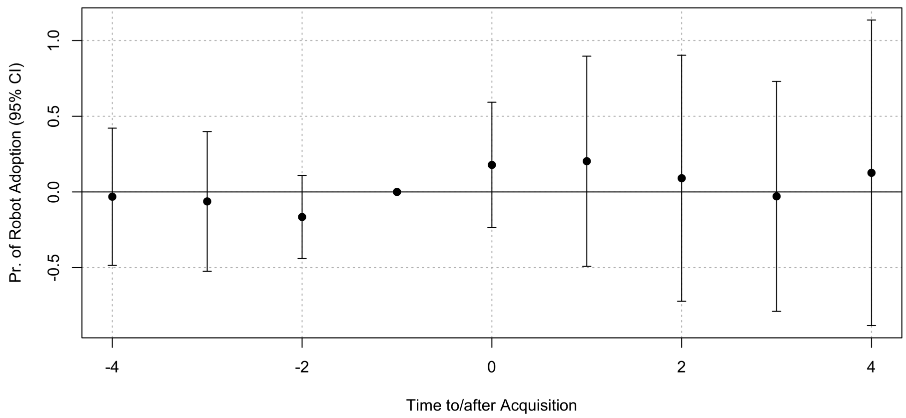
Note: The Figure plots the estimates (and the 95% confidence intervals around them) that I obtain by estimating equation (2) using the log of the exports as outcome variable. I reweigh acquired firms by $1/\widehat{p}$ and non-acquired ones by $1/(1-\widehat{p})$, being $\widehat{p}$ the estimated probability of becoming foreign-owned. The unit of observation is a firm-year pair, and I cluster standard errors by firm. Starting from the first year after the acquisition date, affiliates increase their exports by about 30% compared to the year before the acquisition.

Figure C.6: Covariates' Density Plots by Ownership



Note: This Figure shows the empirical probability density function (pdf) of the log of employees, sales, physical inputs, R&D expenses, wages, and investment by ownership type. I estimate the empirical pdf functions for domestic-owned firms based on their lifetime characteristics. I estimate it only for the years before the acquisition date for those acquired by another domestic firm. Overall, to-be-acquired firms outperform always domestic-owned ones along all dimensions already before the acquisition.

Figure C.7: Event Study (Domestic Acquisitions)

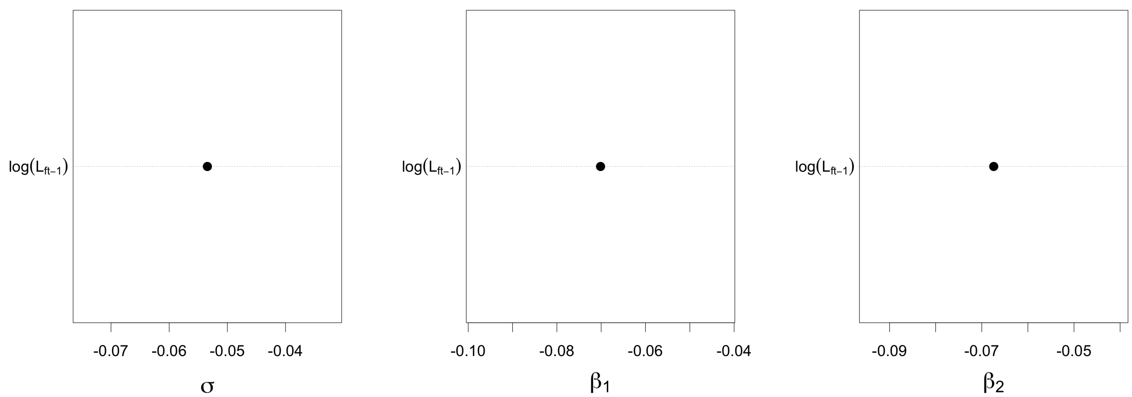


Note: The Figure plots the estimates (and the 95% confidence intervals around them) that I obtain from equation (2). The only difference with the baseline specification is that the O^s_{ft} dummy(-ies) identifies the periods before or after the domestic acquisition date. The unit of observation is a firm-year pair, and I cluster standard errors by firm. The Figure does not deliver any significant effect of being acquired by a Spanish firm on the probability of robot adoption post-acquisition.

Appendix D Additional Model-Related Results

D.1 Figures

Figure D.1: GMM Sensitivity



Note: The Figure shows the sensitivity of σ, β_1 and β_2 in equation (10) to a one-unit of (excluded) instrument standard deviation violation of the moment condition $\mathbb{E}[L_{ft-1}u_{ft}] = 0$. I compute sensitivity using the method of Andrews et al. (2017). Overall, the three estimated coefficients are insensitive to local deviations in this moment condition.

D.2 Counterfactual Scenarios Implementation

I study how the total change in industry-level TFP and labor share (in cost) in the Spanish manufacturing industry over the sample period would have looked like absent robot adoption and/or foreign ownership. To do so, I consider the following system of difference equations based on equations (10) and (12):

$$\log(\widehat{B}_{ft}) = \log(\widehat{B}_{ft-1}) + \widehat{\beta}_1 R_{ft-1} + \widehat{u}_{ft}; \tag{14}$$

$$\log(\widehat{z}_{ft}) = \widehat{\zeta}_0 + \widehat{\zeta}_1 \log(\widehat{z}_{ft-1}) + \widehat{\zeta}_2 R_{ft-1} + \widehat{\zeta}_3 O_{ft-1} + \widehat{\xi}_{ft}. \tag{15}$$

being $\log(\widehat{B}_{ft-1}) = \sum_{s=0}^{4} \left(\log\left(\frac{M_{ft-1}}{L_{ft-1}}\right) - \widehat{\sigma}\log\left(\frac{w_{ft-1}}{r_{jt-1}}\right)\right)^{s}$. Notice that I set $\widehat{\beta}_2 = 0$ in equation (10) because it is not significant in Table 5. I simulate two different scenarios. In the first one, I shut down the effect of foreign ownership on productivity. Second, I shut down both the effect of foreign ownership and that of robot adoption on productivity. In each scenario, I simulate counterfactual outcomes in two steps. First, using the initial (observed) values of total factor and labor-augmenting productivity, I compute the counterfactual TFP and labor share at the firm-year level. Second, I aggregate the results at the industry-year level using the observed firms' employment shares each year, which I keep constant across scenarios. I define industry-level TFP and the industry-level labor share as follows:

$$Z_t = \sum_f \omega_{ft} \log(\widehat{z}_{ft}); \tag{16}$$

$$\begin{aligned} LS_t &= \sum_f \omega_{ft} \frac{w_{ft}L_{ft}}{w_{ft}L_{ft} + r_{ft}M_{ft}} \\ &= \sum_f \omega_{ft} \frac{1}{1 + \frac{w_{ft}L_{ft}}{r_{ft}M_{ft}}} \\ &= \sum_f \omega_{ft} \frac{1}{1 + \left(\frac{w_{ft}}{r_{jt}}\right)^{\widehat{\sigma}-1} \frac{1}{\widehat{B}_{ft}}}. \end{aligned} \tag{17}$$

being ω_{ft} the employment share of firm f in year t in the sub-sample of always active firms. When computing the labor share, I use the relationship implied by the first-order conditions governing the firm-level optimal input mix in equation (8) and hold w_{ft}/r_{jt} at its observed value in the data and simulate $\widehat{B}_{ft}$ using equation (14).

First Scenario - No MNEs

- **Step 1**. I discount the robot adoption coefficients $\widehat{\beta}_1$ in equation (14) and $\widehat{\zeta}_2$ in equation (15). Moreover, I set the effect of foreign ownership on productivity

$\widehat{\zeta}_3 = 0$ in equation (15):

$$\log(\widehat{B}_{ft}) = \log(\widehat{B}_{ft-1}) + \widehat{\beta}_1(1 - \widehat{\theta} \times O_{ft-1})R_{ft-1} + \widehat{u}_{ft}; \tag{18}$$

$$\log(\widehat{z}_{ft}) = \widehat{\zeta}_0 + \widehat{\zeta}_1 \log(\widehat{z}_{ft-1}) + \widehat{\zeta}_2(1 - \widehat{\theta} \times O_{ft-1})R_{ft-1} + \widehat{\xi}_{ft}. \tag{19}$$

The terms $\widehat{\beta}_1(1-\widehat{\theta}\times O_{ft-1})R_{ft-1}$ and $\widehat{\zeta}_2(1-\widehat{\theta}\times O_{ft-1})R_{ft-1}$ capture the indirect effect that foreign-ownership exerts on robot adoption. I use $\widehat{\theta} = 10\%$ from Table 2. Therefore, if $O_{ft-1} = R_{ft-1} = 1$, I discount the foreign-ownership robot adoption premium $\widehat{\theta}$ from the effects of robot adoption on both productivities (i.e,, $\widehat{\beta}_1$ and $\widehat{\zeta}_2$). Remember that I bin the data into seven mutually exclusive time intervals: [1993-1995], [1996-1998], [1999-2001], [2002-2004], [2005-2007], [2008-2010], and [2011-2014]. Because I include one-year lags in equation (18), I can only recover $\widehat{u}_{ft}$ from [1996-1998] onward. Moreover, because I infer $\widehat{z}_{ft}$ from equation (11) and include one-year lags also in equation (19), I can only recover $\widehat{\xi}_{ft}$ from 1998 onward. I simulate equations (18) and (19) forward for [1999-2001], [2002-2004], [2005-2007], [2008-2010], and [2011-2014]. Notice that the effect of shutting down robot adoption compounds over time due to the first-order autoregressive structure of equations (18) and (19).

- **Step 2.** I compute industry-level TFP using equation (16) and the industry-level labor share using equation (17).

Second Scenario - Neither MNEs nor Robots I modify the first-step equations (18) and (19) as:

$$\log(\widehat{B}_{ft}) = \log(\widehat{B}_{ft-1}) + \widehat{u}_{ft}; \tag{20}$$

$$\log(\widehat{z}_{ft}) = \widehat{\zeta}_0 + \widehat{\zeta}_1 \log(\widehat{z}_{ft-1}) + \widehat{\xi}_{ft}. \tag{21}$$

Then, I follow the same steps as in the first scenario.

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