# Automation, trade and multinational activity: Micro evidence from Spain*

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**Abstract**

We use a rich dataset of Spanish manufacturing firms from 1990 to 2016 to shed new light on how automation in in a high-income country affects trade and multinational activity involving less developed countries. By exploiting supply side improvements in the capabilities of robots over time, as described in patents, we show that, in contrast to the speculation that automation will cause 'reshoring', the use of robots in Spanish firms actually had a positive impact on their imports from, and number of affiliates in, less developed countries. Starting to use robots has a positive impact on firm output, productivity and the probability that firms import from, or open affiliates in, less developed countries. The sequencing of automation and offshoring has important consequences for the impact of automation, however. For firms that were importing intensively from less developed countries before they starting to use robots, robot use had no effect on the value of imports, but decreased the share of imports sourced from developing countries. By contrast, for firms that automated first, starting to use robots had a positive impact on the probability that they import from less developed countries and the value of their imports. We show that these findings can be explained in a framework that incorporates firm heterogeneity, the choice between automation, offshoring and performing tasks at home and where automation and offshoring both involve upfront fixed costs, such that their sequencing matters.

**Key words:** Automation, robotics, technology, offshoring, trade, multinationals, global supply chains, heterogeneous firms, labour share, productivity

**JEL codes**: F12, F16, J23, J24

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# 1 Introduction

Recent technical advances in robotics and machine intelligence have been accompanied by a new wave of concern about the consequences of automation. A growing body of literature has been dedicated to examining the impacts of emerging labour-replacing technologies, particularly industrial robots. This research has typically focused on the impacts on domestic labour markets in high-income countries, in isolation from trade patterns and global supply chains (for example, Acemoglu and Restrepo (2019); Graetz and Michaels (2018)). Yet, in a globally integrated economy, it might be expected that automation in one country will not only affect its own labour markets, but also those of its trading partners. Over the past few decades, high-income countries experienced a substantial wave of offshoring of labour intensive manufacturing activities to less developed countries. In a world where production is already conducted offshore, automation in an advanced economy could have an important effect on trade patterns and labour markets in offshore production destinations.

This is a concern that has been emanating from policy institutions and development agencies: that automation technologies might substitute for low-skilled labour in less developed countries, thus reducing the future scope for manufacturing-led development in parts of the world that have yet to industrialise[1]. Manufacturing-led development has been an unrivalled force for poverty reduction. Between 1990 and 2015, 1.2 billion people were lifted out of poverty and of this decline, 93% came from a select group of countries that became heavily integrated in global supply chains over this period – China, India, Korea, Mexico, Poland, Indonesia and Thailand[2]. This question therefore has important implications, yet there is relatively little empirical evidence to date on whether this fear is based on reality, or even how advances in labour-replacing technologies over the past three decades have affected trade and global supply chains involving developing countries.

A key part of understanding the relationship between technological advances that make it easier, or cheaper, to automate production and offshoring is to consider firm level decisions on whether to offshore production stages and whether to invest in labour-replacing technology. In a world of advanced technology and global supply chains, manufacturers increasingly have access to a range of strategies to reduce their production costs. The choice between these strategies depends on their relative costs and benefits. Existing research has tended to study automation at the industry level,

[1] See, for example, Hallward-Driemeier and Nayyar (2017) or Baldwin and Forslid (2020).

[2] Based on the World Bank's US$1.9-a-day poverty line. Poverty data from World Bank Povcalnet http://iresearch.worldbank.org/PovcalNet/data.aspx

missing out on these key firm decisions. To date we, in fact, have surprisingly little empirical evidence about why, and when, firms automate and how it affects firm outcomes, domestic or international.

In this paper we show that firm heterogeneity and dynamics are important for understanding the consequences of automation. We take advantage of a unique dataset of Spanish manufacturing firms that provides both rich information on firm technology use and details on trade and multinational activity between 1990 and 2016. It is well known in the international trade literature that only a small subset of firms export, import or offshore (Bernard et al., 2003, 2009). We show that a similar pattern holds for technology adoption: only a small subset of firms adopt three distinct automation technologies: robots, computer numerically controlled (CNC) machines and flexible manufacturing systems (FMS), but these firms account for the majority of employment, production and trade. For example, in 2014, 33% of the firms in our sample used robots, but these firms accounted for 64% of manufacturing employment, 66% of value added and 72% of exports. Firms that automate also have distinct characteristics: they are on average twice as large, have 60% higher TFP, export and import nearly four times more, are 10% more likely to be a multinational and have a 50% lower labour share than other firms in the same industry, region and year.

We find that prior to having started automating, firms that will select into automating in the future already import more and have more affiliates in all regions, including less developed countries, but import a lower share from less developed countries. This gap is then wider, in any time period, between firms that have automated and those that haven't. Contrary to the typical assumption that automation might cause 'reshoring', we find that firms in our sample were, in fact, more likely to have started automating, using either robots, FMS or CNC machines, before starting to import intensively from, or open affiliates in, less developed countries. When considering robots alone, firms were about as likely to have started using robots before importing intensively from less developed countries as vice versa.

To evaluate the causal impact of automation on trade and multinational activity, we exploit supply-side advances in the capabilities of robots over time that made it technically feasible to automate specific tasks. We follow Webb (2019) and use the text from patent titles to identify the tasks that robot-related patents substitute for, mapped to the occupations frequently conducting those tasks. This allows us to construct time-varying measures of exposure to automation with robots. Using this instrument, we show that for the full sample, starting to use robots in Spain caused firms to increase their value of imports from, and the number of affiliates in, less developed countries. Robot use also

had a positive impact on the extensive margin of trade and multinational activity, leading firms to start importing from or start opening affiliates in less developed countries. For multinational activity, the expansion appears to be more directed at horizontal, rather than vertical, FDI, however, with robot use increasing the probability that the primary activity of the main affiliate is marketing or distribution of products manufactured in Spain, or producing similar products to those manufactured in Spain, as opposed to assembly or adaptation of inputs supplied by the firm in Spain.

We find that the sequencing of automation and offshoring matters. When we focus on firms that were importing intensively from less developed countries before they starting to use robots, we find that robot use had no effect on the value of imports but decreased the share of imports sourced from developing countries, suggesting that automation does, to some degree, shift economic activity away from developing countries, but only for firms that had offshored production first. By contrast, for firms that automate first, starting to use robots has a positive impact on the probability that they import from less developed countries and the value of their imports.

In terms of the consequences for firm operations within Spain, we find that robot use also caused firms to substantially expand production, increase both labour productivity and TFP and decrease their labour share. There is a weak, positive, impact of robot use on employment, but this is not robust to all specifications. Firms that start automating with robots are more likely to report that they have changed their regular workers, and experience a strong increase in the number of engineers and graduates and a weak increase in the number of production workers.

We demonstrate that these key results hold after controlling for import tariff changes, excluding the period of the Global Financial Crisis and excluding the automotive sector. For comparison, we also construct an additional instrument for robots using the capabilities of industrial robots as identified from robot sales data from the International Federation of Robotics (IFR), in a similar way to Graetz and Michaels (2018). We find similar results using this instrument for all outcomes except for the labour share. Finally, we also explore the impact of the intensive margin of automation, finding that increases in the stock of industrial machinery within firms that use robots also had similar impacts to the extensive margin of starting to use robots.

We construct a model that is able to provide a framework for understanding these findings by combining Melitz (2003) style firm heterogeneity with a task based framework for production, similar to Acemoglu and Autor (2011) that incorporates both the decision to automate and the decision to offshore tasks. In a similar vain to Bustos (2011) and Antràs and Yeaple (2014) we model both

technology adoption and offshoring as involving an up-front fixed cost, which provides the basis for why sequencing might matter, but offering a potential marginal cost reduction. An exogenous improvement in the share of tasks that can be automated generates a displacement effect, whereby labour at home or in an offshore location are replaced by machines, and a productivity effect, whereby automation increases productivity and allows firms to expand and demand more labour at home or abroad. Automation hence induces reallocation to the more productive firms at the expense of less productive ones.

This research adds a number of new contributions to the existing, nascent literature on how automation in high income countries affects trade and FDI to less developed ones. There are now a few papers using industry-level robot sales data to study how robot adoption affects country-industry trade flows and Foreign Direct Investment (FDI). Artuc et al. (2018) and Hallward-Driemeier and Nayyar (2019) both show positive impacts of robot intensity in high-income countries on imports sourced from, or FDI growth to, less developed countries, respectively. We contribute by studying this same relationship at the firm level. Our results generally seem to reiterate this finding that the net effect of robot use on imports from less developed countries is positive. We also provide the contribution of offering empirical evidence and a modelling framework to explain the firm dynamics happening in the background: firstly, automation induces scale effects, allowing firms to expand and demand more from less developed countries. Secondly, there are a subset of firms that switch into importing from, or opening affiliates in, less developed countries as a consequence of automation.

Pedemonte et al. (2019), Artuc et al. (2019) and Faber (2018) on the other hand, focus only on trade between the US and Mexico, finding negative effects. Using data on employment or exports in Mexican local labour markets, they show that increased robot penetration in the US reduces exports from Mexico to the US or employment in Maxico. Our research offers some hints as to why these results could hold, despite the other studies finding a positive relationship. Firstly, in our paper the impact of automation differed depending on whether firms first automated or first offshored. If the sample comprised of more firms that offshored first, we might expect a decrease in the share of imports from less developed countries for the full sample. Secondly, our modelling framework suggests that firms that don't automate could lose market share to those that do and in our sample it holds that firms that don't automate, on average, have a higher import share from developing countries. This implies that a large enough market stealing effect could also result in a shift in the composition of imports away from developing countries.

Our paper also contributes to a small but growing literature studying automation using firm level data and evaluating the impact of automation on firm dynamics. Our findings are consistent with the emerging work by Acemoglu et al. (2020) and Aghion et al. (2020) that automation induces within-firm scale and productivity effects. We additionally show that automation leads firms to change their regular workers, increase the wage bill and hire more engineers and graduates. Our results also suggest that studying the impact of automation on domestic outcomes in isolation of trade patterns could lead to incomplete or incorrect conclusions: in our analysis we provide evidence that automation does not only affect domestic outcomes, but the impacts of automation are also passed on to affiliates and trade partners.

This paper is also related to a wider literature studying the effects of robots on labour markets (Acemoglu and Restrepo, 2018, 2019; Bessen et al., 2019; Graetz and Michaels, 2018). Finally, it also contributes to a growing literature studying how different technologies affect trade and global supply chains (Fort, 2017; Steinwender, 2018; Antràs, 2020; Baldwin and Forslid, 2020) and offers a new angle on how labour replacing technologies shape global trade. Finally it contributes to an expanding literature on superstar firms and on the reasons for the decline in the labour share (Autor et al., 2020; Song et al., 2019).

The rest of this paper proceeds as follows. In Section 2, we outline the model and discuss the potential relationship between automation and offshoring. In Section 3 we describe the data used. In Section 4 we exploer the characteristics of firms that automate, the sequencing of automation, importing and multinational activity and conduct an event study design. Section 5 describes the empirical strategy. Section 6 provides the results, Section 7 provides robustness checks and Section 8 concludes.

## 2 Automation and offshoring with heterogeneous firms

This model combines Melitz (2003) style firm heterogeneity with a task based framework building upon Acemoglu and Restrepo (2018). We take inspiration from Bustos (2011) and Antràs and Yeaple (2014), who model technology adoption and offshoring, respectively, in a Melitz framework.

## 2.1 Model setup

There is one monopolistically competitive industry where firms produce differentiated products under increasing returns to scale. Firms are heterogeneous in productivity as in Melitz (2003). Each firm produces a single variety $\omega$ and there is free entry. Firms heterogeneity is reflected by differing 'baseline' marginal costs of production $\varphi(\omega)$. To enter into production, firms pay a fixed entry cost of $f_e$ units of labour. They then draw their productivity from a known Pareto cumulative distribution function $G(\varphi) = 1 - \varphi^{-k}$ with $k > 1$. After observing their productivity firms decide whether to exit or to produce.

## 2.2 Production with offshoring

Following Acemoglu and Restrepo (2018) we assume that production is characterised by combining a unit measure of tasks according to a constant elasticity of substitution aggregator. The production of variety $\omega$ involves performing tasks $x \in [0, 1]$. The output of firm $\omega$ is then:

$$q(\omega) = \varphi(\omega)\left(\int_0^1 q(\omega, x)^{\frac{\sigma-1}{\sigma}} dx\right)^{\frac{\sigma}{\sigma-1}} \tag{1}$$

where $q(\omega, x)$ is the output of task $x$ for firm $\omega$ and $\sigma$ is the elasticity of substitution between tasks.

We depart from Acemoglu and Restrepo (2018) but build upon a variant of Acemoglu and Autor (2011) by assuming that tasks can be performed by either labour at home $l_H(x)$, offshore labour $l_O(x)$ or automated machines $m(x)$. Assume the tasks are ordered by the productivity of home labour in completing them, $\gamma_{LH}(x)$. We begin by assuming that only a subset of tasks $x \in [0, I^O]$ are possible to offshore because there are certain activities that cannot be performed at a distance and these are the tasks that home labour is the most productive in performing. For example, these could be activities that would typically be conducted at the firm headquarters in an advanced country. The tasks that are possible to offshore can be performed by labour at home or offshore labour, but performing a task with offshore labour involves an iceberg transport cost $\tau$ and performing any tasks with offshore labour involves paying a one-off upfront fixed cost $f_O$. Before automation becomes technologically feasible, the output of one task $x$ is then:

$$q(\omega,x)=\begin{cases}\mathbb{1}[H=1]\gamma_{LH}(x)l_H(\omega,x)+\mathbb{1}[O=1]\frac{\gamma_{LO}(x)l_O(\omega,x)}{\tau} & \text{if } x\in[0,I^O]\\ \\ \gamma_{LH}(x)l_H(\omega,x) & \text{if } x\in[I^O,1]\end{cases}$$

where $\gamma_{LH}(x)$ is the productivity of home labour in task x, assumed to be increasing in $x$, $\gamma_{LO}(x)$ is the productivity of offshore labour in task x, $\mathbb{1}[H=1]$ indicates that the firm chooses to conduct the task at home and $\mathbb{1}[O=1]$ indicates that the firm chooses to conduct the task offshore. We assume that $\gamma_{LH}(x)/\gamma_{LO}(x)$ is increasing in $x$ so labour has a comparative advantage relative to offshore labour in higher-indexed tasks. In a similar vain to Acemoglu and Restrepo (2018) we assume that labour in the home country and labour in the offshore country are perfect substitutes.

Combining these equations and defining $\gamma_{LO}^{\tau}$ as the productivity of offshore labour adjusted to take into account iceberg costs, we can write the firm's output if they choose to offshore $q^O(w)$ or if they do not offshore $q(w)$ as:

$$q^O(\omega)=\varphi(\omega)\left(\int_0^{I^O}\left(\gamma_{LO}^{\tau}(x)l_O(\omega,x)\right)^{\frac{\sigma-1}{\sigma}}dx+\int_{I^O}^1\left(\gamma_{LH}(x)l_H(\omega,x)\right)^{\frac{\sigma-1}{\sigma}}dx\right)^{\frac{\sigma}{\sigma-1}} \tag{2}$$

$$q(\omega)=\varphi(\omega)\left(\int_0^1\left(\gamma_{LH}(x)l_H(\omega,x)\right)^{\frac{\sigma-1}{\sigma}}dx\right)^{\frac{\sigma}{\sigma-1}} \tag{3}$$

We denote $\Gamma_F^{(a,b)}=\left(\int_a^b\gamma_F(x)^{\sigma-1}dx\right)$, where F is either $L_O$, $L_H$ or $M$, $F^{(a,b)}(\omega)=\int_a^b f(\omega,x)dx$ where $f$ is either $l_H$, $l_O$ or $m$ then we can rewrite (2) and (3) as:

$$q^O(\omega)=\varphi(\omega)\left(\Gamma_{LO}^{(0,I^O)}L_O^{(0,I^O)}(\omega)^{\frac{\sigma-1}{\sigma}}+\Gamma_{LH}^{(I^O,1)}L_H^{(I^O,1)}(\omega)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} \tag{4}$$

and

$$q(\omega)=\varphi(\omega)\left[\Gamma_{LH}^{(0,1)}L_H^{(0,1)}(\omega)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \tag{5}$$

## 2.3 Preferences

Preferences across varieties have the standard CES form, with an elasticity of substitution $\sigma=1/(1-\rho)>1$. These preferences lead to demand function $q(\omega)=EP^{\sigma-1}[p(\omega)]^{-\sigma}$ for every variety $\omega$

, where $p(\omega)$ is the price of each variety, $P = [\int_0^M p(\omega)^{1-\sigma} d\omega]^{\frac{1}{1-\sigma}}$ is the price index of the industry, $M$ is the number (measure) of existing varieties and $E$ is the aggregate level of spending in the country.

## 2.4 Profit maximisation

The profit maximising price is a constant markup over marginal costs. We begin by considering the scenario where the unit cost of offshore labour is lower than the unit cost of home labour for tasks that are feasible to offshore. This implies that for the marginal task $I^O$ we have that $\frac{\tau w_O}{\gamma_{LO}(I^O)} < \frac{w_H}{\gamma_{LH}(I^O)}$. In this scenario offshoring involves a marginal cost saving relative to using only home labour. In the absence of fixed costs, all firms would therefore offshore all tasks that are feasible to offshore and produce the others at home. In the presence of fixed costs, firms that offshore will offshore all of the tasks that are feasible to offshore. Then the marginal cost if the firm offshores, $MC^O$ or doesn't offshore, $MC$ is:

$$MC^O(\omega) = \frac{1}{\varphi(\omega)} \left( \Gamma_{LO}^{(0,I^O)} w_O^{1-\sigma} + \Gamma_{LH}^{(I^O,1)} w_H^{1-\sigma} \right)^{\frac{1}{1-\sigma}} \tag{6}$$

$$MC(\omega) = \frac{1}{\varphi(\omega)} \left( \Gamma_{H}^{(0,1)} w_H^{1-\sigma} \right)^{\frac{1}{1-\sigma}} \tag{7}$$

Taking the second part of the right hand side of (7), $\left( \Gamma_{H}^{(0,1)} w_H^{1-\sigma} \right)^{\frac{1}{1-\sigma}}$ as the numeraire and equating this to 1, we can then write the marginal cost functions as:

$$MC^O(\omega) = \frac{\alpha}{\varphi(\omega)} \qquad \text{and} \qquad MC(\omega) = \frac{1}{\varphi(\omega)} \tag{8}$$

where $\alpha < 1$ given our assumption that offshoring involves a marginal cost saving relative to using home labour.

### 2.4.1 Productivity cutoff for offshoring

If the firm offshores then they have profit function $\pi^O(\varphi(\omega))$, otherwise they have profit function $\pi(\varphi(\omega))$ as follows:

$$\pi^O(\varphi(\omega)) = (1-\rho) E P^{\frac{\rho}{1-\rho}} \left[ \frac{1}{\rho} MC^O \right]^{\frac{-\rho}{1-\rho}} - F_O - F_e \tag{9}$$

$$\pi(\varphi(\omega)) = (1-\rho)EP^{\frac{\rho}{1-\rho}}\left[\frac{1}{\rho}MC\right]^{\frac{-\rho}{1-\rho}} - F_e \tag{10}$$

And so they will offshore if $\pi^O(\varphi(\omega)) > \pi(\varphi(\omega))$. There is a productivity cutoff $\varphi^*$ associated with offshoring and firms sort into two groups: those which offshore and those which don't. Then denoting $\Omega(\varphi(\omega)) = (1-\rho)EP^{\frac{\rho}{1-\rho}}\left[\frac{1}{\rho}\frac{1}{\varphi(\omega)}\right]^{\frac{-\rho}{1-\rho}}$ we have that firms will offshore when:

$$\pi^O(\varphi(\omega)) - \pi(\varphi(\omega)) > 0 \Leftrightarrow \Omega(\varphi(\omega))(\alpha^{\frac{-\rho}{1-\rho}} - 1) > F_O \tag{11}$$

and $\varphi^*$ is the productivity corresponding to the firm where:

$$\Omega(\varphi^*(\alpha^{\frac{-\rho}{1-\rho}} - 1) = F_O \tag{12}$$

## 2.5 Introducing automation

We next assume that over time there is a subset of tasks $x \in [0, I^M]$ that become technically feasible to automate using existing technologies, such as robots, CNC machines and FMS. We begin by assuming that this subset of tasks is more limited than the subset that can be offshored, because certain tasks are not yet technically feasible to automate, for example, activities involving substantial manual dexterity or handiwork. That is, we assume $I^M < I^O$. Tasks $x \in [0, I^M]$ can be performed by either labour at home, offshore labour or machines. Performing any tasks with machines also involves paying a one-off fixed upfront cost $f_M$. The output of one task $x$ is then:

$$q(\omega, x) = \begin{cases} \mathbb{1}[H=1]\gamma_{LH}(x)l_H(\omega,x) + \mathbb{1}[O=1]\frac{\gamma_{LO}(x)l_O(\omega,x)}{\tau} + \mathbb{1}[M=1]\gamma_M(x)m(\omega,x) & \text{if } x \in [0, I^M] \\ \mathbb{1}[H=1]\gamma_{LH}(x)l_H(\omega,x) + \mathbb{1}[O=1]\frac{\gamma_{LO}(x)l_O(\omega,x)}{\tau} & \text{if } x \in [I^M, I^O] \\ \gamma_{LH}(x)l_H(\omega,x) & \text{if } x \in [I^O, 1] \end{cases}$$

where $\gamma_M(x)$ is the productivity of machines in task x and $\mathbb{1}[M=1]$ is an indicator function denoting that the firm chooses to automate that task. We assume that $\gamma_{LH}(x)/\gamma_M(x)$ and $\gamma_{LO}(x)/\gamma_M(x)$ are

increasing in $x$ so labour at home and abroad has a comparative advantage relative to machines in higher-indexed tasks. We continue to assume that labour in the home country, labour in the offshore country and machines are perfect substitutes. Firms now face two additional prospective output functions for if they choose to automate as well as offshore $q^{OM}$, or if they choose only to automate $q^{M}$:

$$q^{OM}(\omega) = \varphi(\omega)\left( \int_0^{I^M} \left(\gamma_M(x)m(\omega,x)\right)^{\frac{\sigma-1}{\sigma}} dx + \int_{I^M}^{I^O} \left(\gamma_{LO}^{\tau}(x)l_O(\omega,x)\right)^{\frac{\sigma-1}{\sigma}} dx + \int_{I^O}^{1} \left(\gamma_{LH}(x)l_H(\omega,x)\right)^{\frac{\sigma-1}{\sigma}} dx \right)^{\frac{\sigma}{\sigma-1}}$$

$$q^{M}(\omega) = \varphi(\omega)\left( \int_0^{I^M} \left(\gamma_M(x)m(\omega,x)\right)^{\frac{\sigma-1}{\sigma}} dx + \int_{I^M}^{1} \left(\gamma_{LH}(x)l_H(\omega,x)\right)^{\frac{\sigma-1}{\sigma}} dx \right)^{\frac{\sigma}{\sigma-1}} \tag{13}$$

We assume that the unit cost of machines is lower than the unit cost of offshore labour and the unit cost of home labour. This implies that for the marginal task $I^M$ we have that $\frac{r}{\gamma_M(I^M)} < \frac{\tau w_O}{\gamma_{LO}(I^M)}$. In this scenario offshoring involves a marginal cost saving relative to using only home labour and automation involves a marginal cost saving relative to offshoring. In the absence of fixed costs, all firms would therefore automate all of the tasks that are technically feasible to automate, offshore the remainder that are feasible to offshore and produce the others at home. In the presence of fixed costs, firms that choose to automate will automate all of the tasks that are feasible to automate and firms that offshore will offshore all of the tasks that are feasible to offshore.

### 2.5.1 Profit maximisation

As before, the profit maximising price is a constant markup over marginal costs. The firms that have not chosen to automate or offshore therefore charge the highest price, while firms that both automate and offshore charge the lowest price. The marginal costs if the firm offshores and automates, $MC^{OM}$ or only automates, $MC^{M}$ are:

$$MC^{OM}(\omega) = \frac{1}{\varphi(\omega)}\left( \Gamma_M^{(0,I^M)} r^{1-\sigma} + \Gamma_{LO}^{(I^M,I^O)} w_O^{1-\sigma} + \Gamma_{LH}^{(I^O,1)} w_H^{1-\sigma} \right)^{\frac{1}{1-\sigma}} \tag{14}$$

$$MC^M(\omega) = \frac{1}{\varphi(\omega)} \left( \Gamma_M^{(0,I^M)} r^{1-\sigma} + \Gamma_{LH}^{(I^M,1)} w_H^{1-\sigma} \right)^{\frac{1}{1-\sigma}} \tag{15}$$

Once again taking the marginal cost without automation or offshoring as the numeraire we can write these marginal cost functions as:

$$MC^{OM}(\omega) = \frac{\beta}{\varphi(\omega)} \qquad \text{and} \qquad MC^M(\omega) = \frac{\delta}{\varphi(\omega)} \tag{16}$$

Our assumption that automation involves a marginal cost reduction relative to offshoring implies that $\beta < \alpha < 1$, while we also have that $\beta < \delta$ and $\delta < 1$. The rank of $\alpha$ relative to $\delta$, on the other hand, depends on the task subset that is feasible to automate, $I^M$ relative to the subset feasible to offshore, $I^O$ and the rental rate $r$ relative to the cost of offshore labour $w_O$.

To make the decision of whether to conduct tasks using only home labour, offshore labour, machines, or both offshore labour and machines, firms compare the profits under each option. Their profit functions if they automate, $\pi^M(\varphi(\omega))$, or if they offshore and automate, $\pi^{OM}(\varphi(\omega))$ are as follows:

$$\pi^M(\varphi(\omega)) = (1-\rho) E P^{\frac{\rho}{1-\rho}} \left[ \frac{1}{\rho} MC^M \right]^{\frac{-\rho}{1-\rho}} - F_M - F_e \tag{17}$$

$$\pi^{OM}(\varphi(\omega)) = (1-\rho) E P^{\frac{\rho}{1-\rho}} \left[ \frac{1}{\rho} MC^{OM} \right]^{\frac{-\rho}{1-\rho}} - F_M - F_O - F_e \tag{18}$$

There are now two additional productivity cutoffs associated with automating $\varphi^{M*}$ and both automating and offshoring $\varphi^{OM*}$. Firms sort into four different groups depending on their productivity: the lowest productivity firms produce but do not automate or offshore, those with medium productivity either automate or offshore, and the highest productivity firms both automate and offshore. The benefit of automating and offshoring is firms earn higher revenues, because consumer demand is elastic ($\sigma > 1$), but firms must pay the higher fixed cost. The benefits of automating or offshoring are also increasing in firm productivity.

## 2.6 Advances in automation

This model allows for three types of technological progress in automation:

1. The extensive margin of automation: an increase in $I^M$.

2. The intensive margin of automation: an increase in $\gamma_M(x)$ or a decrease in $r$.

3. The fixed cost of automation: a decrease in $f_M$.

Here we focus on the extensive margin, as characterised by the invention of new technologies capable of automating a wider variety of tasks.

### 2.6.1 Firm level implications

At the firm level, holding $I_O$ fixed, an increase in $I_M$ has the following effect:

- **Firms that are already automating** will conduct more tasks using machines, reducing demand for offshore labour or labour at home. However, the improvement will also lower marginal costs, meaning that the firms that automate can reduce prices, increase revenues and expand, increasing demand for offshore labour or home labour in the tasks that can't be automated. Automation at the extensive margin in our model therefore has the same two counteracting effects as in Acemoglu and Restrepo (2018) that affect both demand for offshoring and for home labour within the firm: the negative displacement effect and the positive productivity effect.

- **Firms that are induced to automate** because of the further marginal cost reduction of being able to use machines for more tasks will experience a larger displacement effect as they switch a whole subset of tasks $x \in [0, I^M]$ away from home labour or offshore labour and towards machines and also a positive productivity effect.

- **Firms that do not automate** decrease output, home employment and offshoring if they have offshored. They face no displacement but a negative productivity effect.

### 2.6.2 Industry level implications:

An expansion in the task subset that can be automated reduces the productivity cutoff associated with automating and so raises industry level automation. In turn this raises the survival cutoff, meaning that firms that cannot automate are forced to exit and surviving non-automating firms reduce their output, employment and offshoring. In the world with more automation, the expected productivity level of surviving firms is therefore higher than in the world without automation and the per period expected profits of surviving firms are also higher.

# 3 Data

## 3.1 Spanish firms data

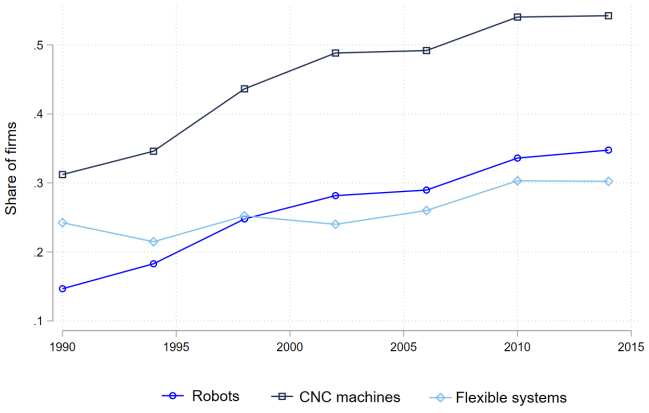
The primary data source is the "Encuesta Sobre Estrategias Empresariales" (ESEE), an annual survey of Spanish manufacturing firms carried out by the SEPI Foundation in conjunction with the Spanish Ministry of Industry[3] between 1990 and 2016. This dataset is unique in providing a rich set of variables on firm technology use and information on trade and multinational activity. The survey generates an unbalanced panel of 5,840 legal entities for the years 1990-2016. The SEPI Foundation applies a complex random sampling procedure, sending out survey questionnaires to all firms with more than 200 employees, and to a subset of firms with 200 or less but more than 10 employees. This subset is selected according to a stratified sampling scheme that guarantees that they can establish representativeness of the data for different industries and the manufacturing sector as a whole. The SEPI Foundation preserves these sample properties over time by controlling for the dynamics in the panel due to market entry and exit. In total there are 49,237 firm-year observations, with an average of 1824 firms in each year and a median duration in the sample of six years.

**Automation related variables:** The dataset provides dummy variables on firm use of three distinct technologies related to automation: robots, CNC machines and FMS. These variables are reported for four year periods. The dataset also asks about firm use of Computer Aided Design/Computer Aided Manufacturing (CAD/CAM), but in our analysis we don't include CAD/CAM as CAD/CAM is a process and software that is typically combined with CNC machines, where CNC machines are the machinery that conducts the task. A description of these technologies is as follows:

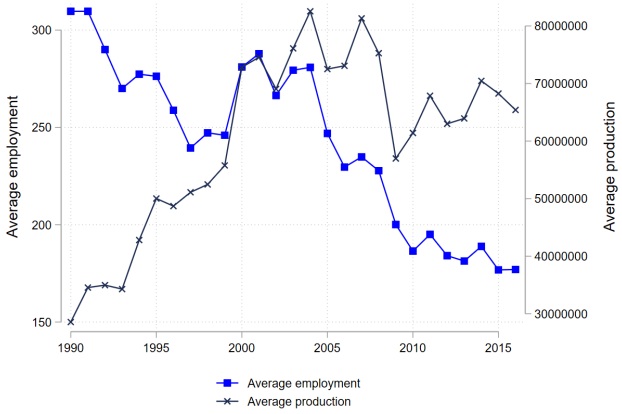
1. **Robots:** Robots can perform many industrial applications including welding, material handling, assembly, palletizing, and painting. The International Federation of Robotics (IFR) defines industrial robots by the ISO 8373 definition: 'An automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which may be either fixed in place or mobile for use in industrial automation applications'

2. **FMS:** An FMS combines CNC machines, industrial robots, and other types of automation into

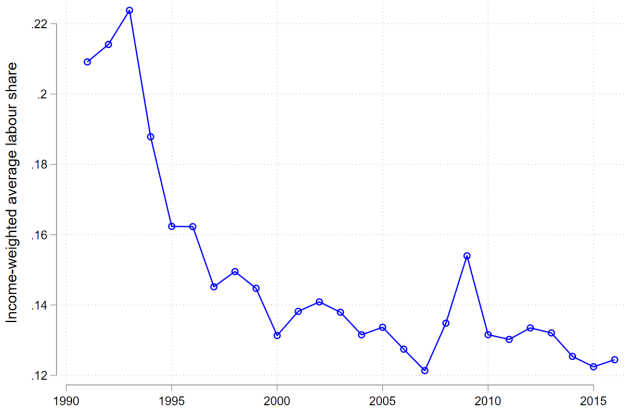
[3] https://www.fundacionsepi.es/investigacion/esee/en/spresentacion.asp



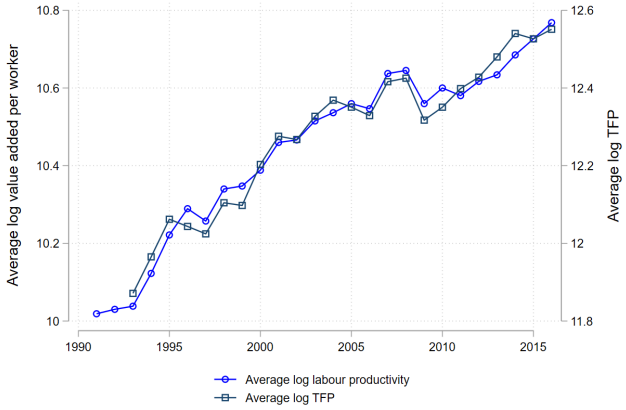

(a) Technology adoption




(b) Employment and production




(c) Labour share




(d) Productivity

Figure 1: Key domestic outcomes over time

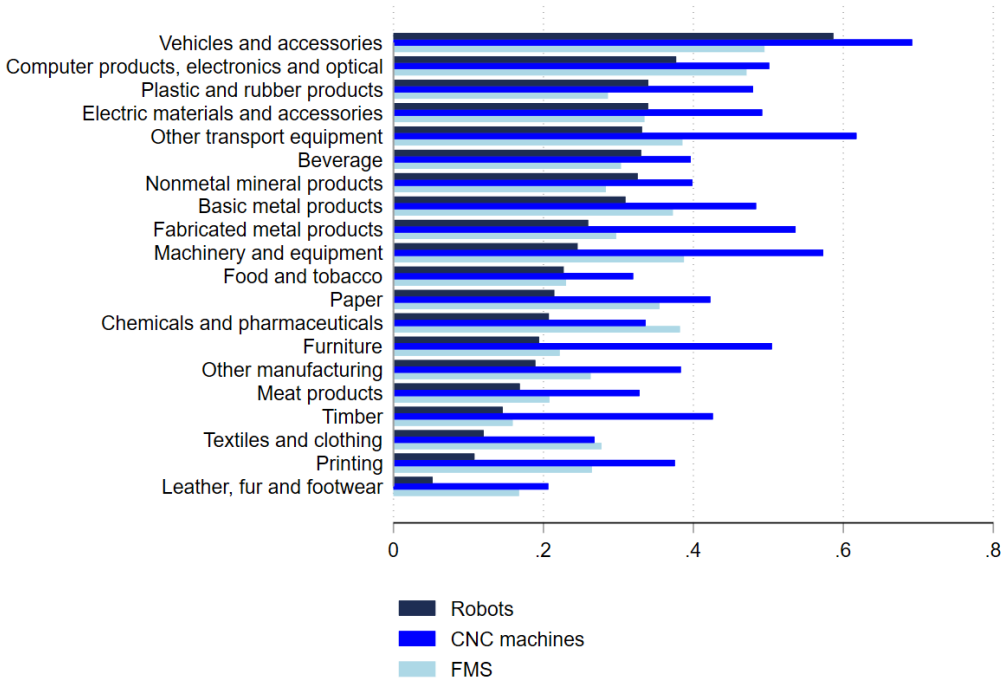



Figure 2: Share of firms using each technology, by industry

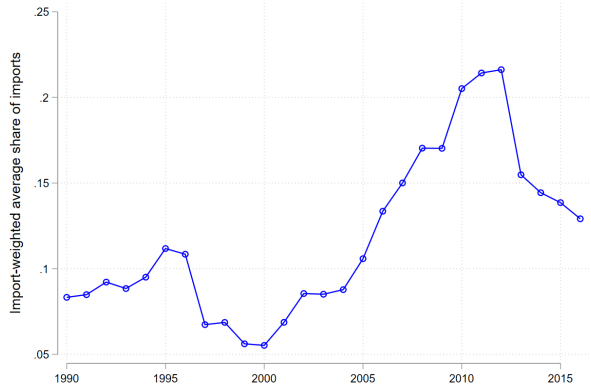
one fully automated system. A FMS would typically produce similar products and parts but still maintain the flexibility to change parts or processes.

3. **CNC Machines:** CNC machines use computers to store, calculate, and execute operations that are usually performed by hand. A common example of a CNC machine is a CNC mill, which uses computers to analyze, cut, and mill each piece of material.

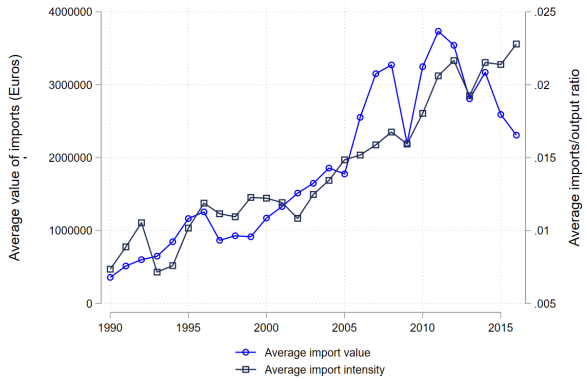
Figure 1(a) displays the share of firms using these technologies over time and Figure 2 displays the share using these technologies on average across all years by industry[4]. There are 20 industries in the ESEE data using the Spanish NACECLIO classification system, which is based on the NACE[5]. The share of firms using robots and CNC machines has approximately doubled over our sample period, while the share using FMS has risen more moderately. The most automated industries are Vehicles and Accessories, Computer Products, Electronics and Optical and Plastic and Rubber Products, while the least automated are Leahter, Fur and Footwear, Printing and Textiles and Clothing.

[4]In the Appendix, Figure 7 also displays technology adoption by region.

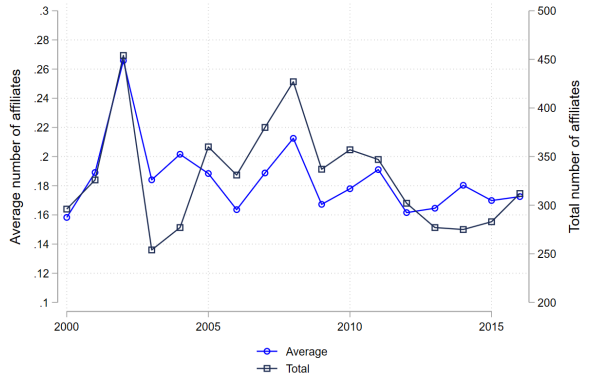
[5]These industries are meat related products; food and tobacco; beverage; textiles and clothing; leather, fur, and footwear; timber; paper; printing and publishing; chemicals; plastic and rubber products; nonmetal mineral products; basic metal products; fabricated metal products; industrial and agricultural equipment; office machinery, data processing, precision instruments and similar; electric materials and accessories; vehicles and accessories; other transportation materials; furniture; other manufacturing.



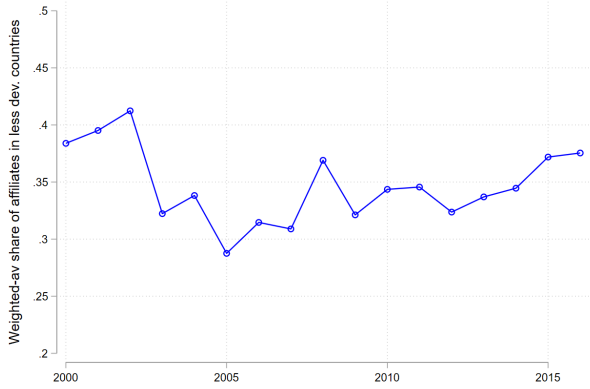

(a) Import share from less dev. countries




(b) Value of imports & import intensity




(c) Affiliates in less dev. countries




(d) Share of affiliates in less dev. countriess

Figure 3: Key international outcomes over time

Additionally the ESEE data provides investment by type, with one of the categories 'Industrial machinery and equipment'. We use this, along with the firm level depreciation rate, to construct the firm level stock of industrial machinery and equipment.

**Trade and multinational activity variables:** The key trade-related variables we use are the value of imports and breakdown of imports by region. Firms provide exports and imports broken down into region groups: the EU, OECD countries excluding the EU, Latin America and the Rest of World. We combine the sum of Latin-America and Rest of World to form a broad measure of trade with 'less developed countries'[6]. We then use the variables of whether a firm imports from this group of countries, the share of imports from this group and the intensity of imports from this group, measured as imports as a share of production.

Additionally, firms provide their number of affiliates by these same region groups, the country of the

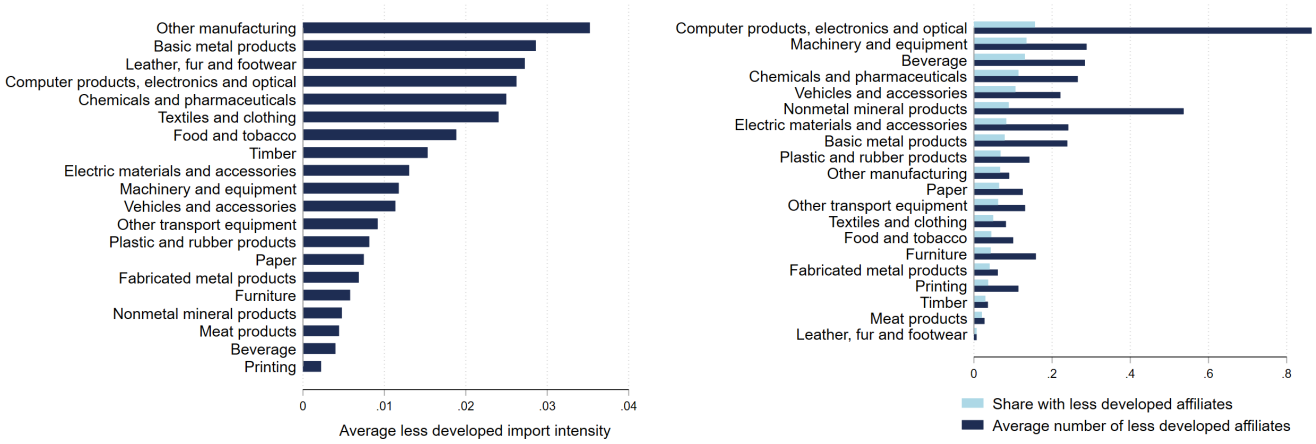
[6]Spain's largest import partners in this group are China, Morocco, Algeria, Nigeria, India, Brazil, Russia, Vietnam, Bangladesh, Saudi Arabia and Indonesia.

main affiliate, employment at the main affiliate and information on the activities of affiliates. They ask whether the main activity of the affiliated company consists only of commercialisation or distribution, whether the main affiliated company manufactures similar products to those manufactured in Spain by its company or whether the main affiliated company carries out adaptation and/or assembly activities of parts provided by the company in Spain. In our baseline analysis we focus on two key variables: the number of affiliates in less developed countries and the share of affiliates in less developed countries. We then explore changes in the employment and main activities as a secondary exercise.

Our model framed our analysis in terms of 'offshoring' of tasks. There are a range of definitions of offshoring that have been used in the literature. Blinder and Krueger (2013) define offshoring as 'The movement of home-country jobs to another country'. Hummels et al. (2014) define it as 'The import of intermediate inputs that could have been produced within the same firm'. Feenstra and Hanson (1999) distinguish between narrow and broad offshoring, where the former considers imported intermediates in a given industry from the same industry only, while the latter considers imported intermediates from all industries. Our import variable is not only intermediate imports, but all firm imports, so is slightly broader than these definitions. However, from the year 2006 onwards, the ESEE data starts to ask firms about the share of their imports that are imported inputs. The median response is that 75% of imports are imported inputs, suggesting that our import variable is a close proxy measure of 'broad' offshoring.

Figure 3 displays the key trade and multinational activity variables over time. Between 1990 and 2016 the mean value of imports from less developed countries and the intensity of imports from less developed countries, have increased approximately six-fold[7]. The import-weighted share of imports from less developed countries approximately tripled between 1990 and 2010 but has then fallen. There is a less clear pattern for affiliates in less developed countries. Figure 4(a) displays the import intensity from less developed countries by industry. The industries with the highest import intensity are Other Manufacturing, Basic Metal Products and Leather, Fur and Footwear. Figure 4(b) displays the share of firms with affiliates in less developed countries and the average number of affiliates in less developed countries, by industry. The three industries with the highest share of firms having affiliates in less developed countries are Computer products, electronics and optical, Machinery and equipment and Beverage.

[7]The same holds for the total value of imports from less developed countries across all firms included in the data




(a) Import intensity

(b) Affiliates

Figure 4: Mean less developed import intensity, share with affiliates & no. of affiliates, by industry

**Measuring TFP:** We measure TFP using the Levinsohn- Petrin method, which overcomes the endogeneity problem associated with estimating TFP using OLS by using intermediate inputs to control for unobserved productivity changes. We choose this method over Olley-Pakes, which uses investment as the control variable, because investment is often reported as zero (in our sample it is zero in just over 20% of observations). The ESEE data includes both gross and net capital stock, firm level depreciation and investment, allowing for precise measurement of the capital stock. Additionally it includes firm level changes in input and output prices. It asks firms about the annual change in the sales price of their products, the change in the purchased price of energy, raw materials and services. Following Beveren (2012) we control for input and output prices. We use the sales price change to deflate firm sales and the average of the change in energy and raw materials prices to deflate the value of intermediate inputs.

**Employment categories:** In addition to providing total employment, the data also includes employment by a number of categories: the share of engineers and graduates, the share of non-graduates, the share of production workers and the share of clerical workers, where clerical workers is defined to include managerial staff and administrative staff.

**Other variables:** The main analysis also explores how automation affects total employment, output, which is defined as the total value of production of goods and services, value added per

TABLE 1. SUMMARY STATISTICS

| | mean | sd | min | max |
|---|---|---|---|---|
| Robot user | 0.27 | 0.44 | 0 | 1 |
| FMS user | 0.28 | 0.45 | 0 | 1 |
| CNC machine user | 0.45 | 0.50 | 0 | 1 |
| Robot user log machinery stock | 4.35 | 7.02 | 0 | 44.6 |
| Patent exposure measure | 33.8 | 20.1 | 5.00 | 118.4 |
| IFR exposure measure | 0.28 | 0.26 | 0 | 0.89 |
| IFR stock | 915333 | 336949 | 557516 | 1828024 |
| Share of imports from less dev countries | 0.44 | 0.47 | 0 | 1 |
| IHS(imports from less dev countries) | 3.03 | 5.82 | 0 | 21.9 |
| IHS(import intensity from less dev countries) | 0.014 | 0.053 | 0 | 1.21 |
| IHS(affiliates in less dev countries) | 0.092 | 0.39 | 0 | 5.30 |
| Share of affiliates in less dev countries | 0.043 | 0.18 | 0 | 1 |
| Log employment | 4.20 | 1.50 | 0 | 10.1 |
| Log output | 15.8 | 2.03 | 8.59 | 22.9 |
| Labour share | 0.29 | 0.35 | 0.0049 | 59.0 |
| Log labour productivity | 10.4 | 0.72 | 1.50 | 15.2 |
| Log TFP | 12.3 | 1.24 | 1.21 | 17.9 |

Notes: This table shows the summary statistics for the key variables used in the main empirical analysis, pooled across all years.

worker and the labour share of income.[8] Figure 1 displays the evolution of these variables over the sample period. Table 1 displays the summary statistics for the key variables used in the analysis.

## 3.2 Spanish employment data

We obtain data on the composition of employment in 1981 by 2 digit ISCO 68 occupation code within each industry and region from IPUMS International, which obtains its data from the Spanish Census of Population and Housing 1981. This census covers a 5% sample of the population. We choose the 1981 sample because we are studying the impact of automation on offshoring and thus want the employment composition before offshoring began on a large scale. Ideally we would like to use the full sample of employment by industry, region and occupation, but this does not exist for Spain at a detailed enough level of disaggregation. The Census of Housing and Population is the most comprehensive data source on employment in these three dimensions.

[8]Following consensus in the literature we define the labour share as the sum of all labour costs divided by total income.

### 3.3 Patent and occupation data

The construction of the robot exposure measures as in Webb (2019) uses Google Patents Public Data, provided by IFI CLAIMS Patent Services[9]. The fields used are the title, abstract, and CPC codes, as described further below. The O*NET database, produced by the US Department of Labor, is also used as the source of information on occupations. O*NET describes 964 occupations. A set of tasks is listed for each occupation, described in natural language. Each task is also given scores that indicate its importance and frequency in the occupation. These scores are used to weight tasks within occupations. The method for constructing patent-occupation text similarity is outlined in Section 5.

### 3.4 IFR robot sales data

We also make use of data from the IFR. The IFR measures global shipments of 'multipurpose manipulating industrial robots', based on the definition of the International Organization for Standardization (ISO) 8373: 'An automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which may be either fixed in place or mobile for use in industrial automation applications'. The IFR data includes shipments delivered to each country by industry and application for the time period 1993-2016. Typical applications of industrial robots include assembling, dispensing, handling, processing (e.g., cutting), and welding, all of which are prevalent in manufacturing industries. We use this data to construct additional robot exposure measures, closely following the method of Graetz and Michaels (2018), discussed further in Section 5.

### 3.5 Import tariff controls

As a robustness check, we additionally use a control variable for changes to import tariffs that may have affected imports from less developed countries or affiliates in less developed countries. We follow the method used by Chen and Steinwender (2019), which exploits the fact that tariffs for Spain are set at the EU level and hence plausibly exogenous. We construct two industry-year level variables for MFN import tariffs on goods in the same industry ('same industry import tariffs') and MFN import tariffs on the imported inputs used by that industry ('imported input tariffs'). We take the data for MFN tariffs from TRAINS (provided by UNCTAD) accessed via the WITS platform from the World

[9]https://bigquery.cloud.google.com/table/patents-public-data:patents.publications 201710

TABLE 2. PREVALENCE AND MARKET SHARE OF FIRMS THAT AUTOMATE

| | 1990 | 2002 | 2014 | 1990 | 2002 | 2014 | 1990 | 2002 | 2014 |
|---|---|---|---|---|---|---|---|---|---|
| | Robots | | | CNC machines | | | FMS | | |
| | Total number of firms | | | | | | | | |
| Don't use | 1856 | 1,638 | 1375 | 1494 | 1,177 | 956 | 1651 | 1,733 | 1450 |
| Use | 321 | 669 | 686 | 683 | 1,128 | 1105 | 518 | 574 | 611 |
| % using | 15% | 29% | 33% | 31% | 49% | 54% | 24% | 25% | 30% |
| | Total employment (millions) | | | | | | | | |
| Don't use | 0.29 | 0.18 | 0.10 | 0.24 | 0.13 | 0.09 | 0.29 | 0.21 | 0.12 |
| Use | 0.24 | 0.28 | 0.19 | 0.29 | 0.32 | 0.18 | 0.34 | 0.25 | 0.16 |
| % using | 46% | 61% | 64% | 56% | 71% | 67% | 54% | 54% | 57% |
| | Total sales (Euro billions) | | | | | | | | |
| Don't use | 28.1 | 37.1 | 36.1 | 29.0 | 31.9 | 26.1 | 19.2 | 43.4 | 36.3 |
| Use | 31.2 | 80.1 | 71.6 | 30.3 | 85.3 | 81.7 | 40.1 | 73.8 | 71.4 |
| % using | 53% | 68% | 66% | 51% | 73% | 76% | 68% | 63% | 66% |
| | Total exports (Euro billions) | | | | | | | | |
| Don't use | 4.8 | 10.4 | 16.3 | 4.1 | 7.8 | 11.5 | 2.8 | 12.4 | 16.3 |
| Use | 4.9 | 33.6 | 41.2 | 5.7 | 36.1 | 46.1 | 6.9 | 31.6 | 41.3 |
| % using | 51% | 76% | 72% | 58% | 82% | 80% | 71% | 72% | 72% |
| | Total imports (Euro billions) | | | | | | | | |
| Don't use | 3.47 | 6.74 | 8.79 | 2.9 | 5.4 | 4.1 | 1.95 | 8.47 | 6.54 |
| Use | 5.56 | 23.3 | 24.6 | 6.1 | 24.6 | 29.3 | 7.07 | 21.6 | 26.8 |
| % using | 62% | 78% | 74% | 67% | 82% | 88% | 78% | 72% | 80% |

Notes: This table shows the total number of firms, the total number of employees, the sum of the value added, production and exports of all firms in the sample, broken down by whether or not they use robots, CNC machines and FMS, in a given time period.

Bank[10]. We take the simple average tariff in each ISIC Rev 3 product category in each year and use an ISIC Rev 3-NACE Rev 1 Crosswalk provided by Eurostat[11] to map these to NACE Rev 1 industries. We then use UNCOMTRADE data from WITS on Spanish imports in 1990 by ICIC Rev 3 to create baseline-import weighted average tariffs for each NACE Rev 1 industry. The ESEE data uses the Spanish NACECLIO industry classification, which is based upon NACE so we can easily map NACE Rev 1 to the industries in the ESEE data. For the imported input tariffs we further weight these tariffs using the IO import table weights obtained from the Instituto Nacional D'Estistica (INE). [12]

# 4 Which firms automate?

We begin by documenting the characteristics of firms that use robots, FMS and CNC machines over time. Our modelling framework incorporates Melitz (2003) style heterogeneity and here we

[10] wits.worldbank.org

[11] https://ec.europa.eu/eurostat/ramon/relations/index.cfm?TargetUrl=LST_REL

[12] https://www.ine.es/dyngs/INEbase/en/operacion.htm?c=Estadistica_C&cid=1254736177058&menu=enlaces&idp=1254735576581

TABLE 3. TECHNOLOGY ADOPTION PREMIA

| | 1994 | 2002 | 2014 | 1994 | 2002 | 2014 | 1994 | 2002 | 2014 |
|---|---|---|---|---|---|---|---|---|---|
| | Robots | | | CNC machines | | | Flexible systems | | |
| | Panel (a): Firm characteristics | | | | | | | | |
| Log total employment | 1.35 | 1.37 | 1.06 | 0.93 | 0.85 | 0.62 | 1.29 | 1.09 | 0.91 |
| Log value added per worker | 0.19 | 0.29 | 0.25 | 0.13 | 0.19 | 0.15 | 0.29 | 0.23 | 0.25 |
| Log TFP | 0.74 | 0.81 | 0.63 | 0.50 | 0.48 | 0.34 | 0.77 | 0.64 | 0.57 |
| Log output | 1.70 | 1.79 | 1.40 | 1.18 | 1.06 | 0.86 | 1.68 | 1.42 | 1.27 |
| Labour share (%) | -0.039 | -0.060 | -0.078 | -0.047 | -0.036 | -0.035 | -0.051 | -0.043 | -0.047 |
| | Panel (b): International Trade | | | | | | | | |
| Exporter | 0.28 | 0.27 | 0.17 | 0.18 | 0.17 | 0.12 | 0.22 | 0.19 | 0.14 |
| Importer | 0.27 | 0.27 | 0.18 | 0.19 | 0.16 | 0.11 | 0.26 | 0.17 | 0.16 |
| IHS(exports) | 5.40 | 5.54 | 3.73 | 3.29 | 3.22 | 2.52 | 4.22 | 3.93 | 3.14 |
| IHS(imports) | 4.97 | 5.15 | 3.70 | 3.25 | 2.96 | 2.23 | 4.65 | 3.38 | 3.31 |
| IHS(imports from less developed) | 1.57 | 1.70 | 2.53 | 1.03 | 1.15 | 1.76 | 1.50 | 1.85 | 2.03 |
| Import share from less developed | -0.27 | -0.26 | -0.15 | -0.18 | -0.15 | -0.086 | -0.22 | -0.15 | -0.14 |
| | Panel (c): Multinational activity | | | | | | | | |
| Multinational | 0 | 0.15 | 0.11 | 0 | 0.066 | 0.051 | 0 | 0.082 | 0.097 |
| IHS(total number of affiliates) | 0 | 0.24 | 0.21 | 0 | 0.11 | 0.12 | 0 | 0.18 | 0.16 |
| IHS(number of less developed affiliates) | 0 | 0.10 | 0.092 | 0 | 0.039 | 0.073 | 0 | 0.099 | 0.062 |

Notes: this table shows the coefficients from regressions of the dependent variables listed on the left hand side on a dummy variable for firm use of one of the three technologies in the specified year. All coefficients are significant to the 1 % level. These regressions also included industry and region fixed effects. We take the Inverse Hyperbolic Sine (IHS) transformation due to the presence of zeros. Standard errors were clustered at the industry-region level in all regressions.

demonstrate why this is an important aspect for understanding the causes and consequences of automation. In terms of market share, manufacturing firms using our three technologies are in the minority, but make up the majority of employment, sales, value added and exports, as is shown in Table 2. In 1990 15 percent of the firms in the sample used robots, but accounted for 46 percent of employment, 53 percent of value added and output and 51 percent of exports. The proportion of firms using CNC machines is higher than all other technologies.

## 4.1 The performance gap for firms that automate

We further document the performance gap for firms that use these technologies compared with firms that don't. We report these differences in Table 3 for three time periods (1994, 2002 and 2014). This table reports the technology adoption 'premia' estimated from a regression of the form:

$$X_i = \alpha + \beta \text{Technology}_i + \gamma \text{Industry}_i + \theta \text{Region}_i + \epsilon_i \tag{19}$$

where $X_i$ is the outcome of interest, $\text{Technology}_i$ is a dummy variable for firm use of one of the three technologies: robots, CNC or FMS, $\text{Industry}_i$ is the firm's 2 digit industry and $\text{Region}_1$ is

the Spanish autonomous community where the firm is headquartered[13]. Each premium shows the average difference between firms in the same industry and region using or not using that specific technology. Panel (a) of Table 3 shows that there is a premium for all of the technologies in all of the time periods for all firm characteristics listed. Across all the technologies and time periods, firms using these technologies employ approximately twice the number of workers, have 22% higher labour productivity, 60% higher TFP, produce more than double and have a labour share that is 0.05 lower. However, the size and productivity premia tend to be decreasing over time, suggesting that barriers to automating might have been decreasing over time.

Panel (b) of Table 3 shows the difference in international orientation for firms using these technologies. In all time periods, firms using these technologies are on average 20% more likely to be exporters or importers, import and export nearly four times more to all destinations, import nearly twice as much from less developed countries but the share of their imports from less developed countries is around 17% lower. Interestingly the negative premium in terms of import share from less developed countries has reduced over time, suggesting some potential for substitutability between automating and importing from less developed countries in the earlier periods, or a relationship between the origin of trade and productivity, that has been decreasing over time. Panel (c) shows that firms that automate are, on average, also 6% more likely to be multinational corporations, have around 11% more affiliates on average and 5% more affiliates in less developed countries. The premia for the share of affiliates in less developed countries were not statistically significant.

## 4.2 Selection into automation

While it is clear that firms that automate have distinct characteristics, it is not clear if this is the impact of automation or a selection effect. We hence also consider the characteristics of firms that will select into automating in the future, prior to having started. We calculate the *ex ante* premia for firms that will use these technologies in the future, but do not yet use them in the present, relative to firms in the present who never adopt these technologies in the sample period. Table 4 documents the coefficients for regressions of the form:

$$X_{it} = \alpha + \beta \text{FutureTechnology}_{it} + \gamma \text{Industry}_{it} + \theta \text{Region}_{it} + \epsilon_{it} \tag{20}$$

[13]The ESEE data includes 20 regions

TABLE 4. FUTURE TECHNOLOGY ADOPTION PREMIA

| | 1994 | 2002 | 2010 | 1994 | 2002 | 2010 | 1994 | 2002 | 2010 |
|---|---|---|---|---|---|---|---|---|---|
| | Robots | | | CNC machines | | | Flexible systems | | |
| | Panel (a): Firm characteristics | | | | | | | | |
| Log total employment | 1.14 | 0.86 | 0.90 | 0.84 | 0.75 | 0.68 | 1.04 | 0.86 | 0.95 |
| Log value added per worker | 0.27 | 0.21 | 0.18 | 0.27 | 0.20 | 0.21 | 0.27 | 0.35 | 0.26 |
| Log TFP | 0.66 | 0.55 | 0.59 | 0.52 | 0.52 | 0.56 | 0.64 | 0.61 | 0.60 |
| Log output | 1.49 | 1.17 | 1.18 | 1.22 | 1.10 | 1.01 | 1.39 | 1.16 | 1.29 |
| Labour share (%) | -0.059 | -0.060 | -0.073 | -0.078 | -0.066 | -0.072 | -0.063 | -0.048 | -0.064 |
| | Panel (b): International Trade | | | | | | | | |
| Exporter | 0.24 | 0.20 | 0.18 | 0.19 | 0.17 | 0.16 | 0.23 | 0.20 | 0.18 |
| Importer | 0.25 | 0.20 | 0.22 | 0.22 | 0.17 | 0.13 | 0.25 | 0.21 | 0.17 |
| IHS(exports) | 4.20 | 3.60 | 3.54 | 3.35 | 2.89 | 3.13 | 4.01 | 3.80 | 3.68 |
| IHS(imports) | 4.29 | 3.56 | 3.81 | 3.47 | 2.95 | 2.49 | 4.14 | 3.52 | 3.19 |
| IHS(imports from less developed) | 0.90 | 0.98 | 1.62 | 1.01 | 1.41 | 1.09 | 1.14 | 0.91 | 1.06 |
| Import share from less developed | -0.24 | -0.19 | -0.21 | -0.19 | -0.15 | -0.11 | -0.23 | -0.20 | -0.16 |
| | Panel (c): Multinational activity | | | | | | | | |
| Multinational | | 0.080 | 0.092 | | 0.062 | 0.083 | | 0.13 | 0.12 |
| IHS(total number of affiliates) | | 0.14 | 0.11 | | 0.12 | 0.11 | | 0.21 | 0.17 |
| IHS(number of less developed affiliates) | | 0.060 | 0.046 | | 0.070 | 0.040 | | 0.080 | 0.077 |

Notes: this table shows the coefficients from regressions of the dependent variables listed on the left hand side on a dummy variable for if a firm begins using one of the three technologies. The sample is limited to firms not using these technologies in the present. These regressions also controlled for industry and region dummy variables. All coefficients were significant to the 5% level. Standard errors were clustered at the industry-region level in all regressions.

where $X_{it}$ is the outcome of interest for firm $i$ in period $t$, $FutureTechnology_{it}$ is a dummy variable for firm use in the future of one of the technologies: robots, CNC machines or FMS, $Industry_{it}$ is firm $i$'s 2 digit industry at time $t$ and $Region_{it}$ is the Spanish autonomous community where firm $i$ is headquartered at time $t$. The sample is limited to firms not currently using the given technology. Each premium shows the average difference between firms in the same industry and region that start adopting the specific technology in the future compared to those that never adopt it.

Table 4 displays all of the premia that are statistically significant to the 5% level, showing that the distinct characteristics of technology adopters also hold before adoption happens. However, these premia tend to be lower and less statistically significant than for actual adopters, suggesting that automation might also have a causal impact on these firm outcomes, or firms that adopt technology sooner rather than later also have distinct characteristics. Particularly interestingly for our analysis, the ex ante premia for the value of imports from less developed countries is only two thirds of that for the current adopter premia and the two premia are statistically significantly different.

TABLE 5. SEQUENCING OF AUTOMATION, IMPORTING AND OPENING AFFILIATES

| Panel (a): Automates using robots, CNC machines or FMS | | | |
|---|---|---|---|
| Importing intensively from less developed countries | | Opening affiliates in less developed countries | |
| Sequencing | Share of firms | Sequencing | Share of firms |
| First automates then imports | 16% | First automates, then opens affiliates | - |
| First imports then automates | 8% | First opens affiliates, then automates | - |
| Both at same time | 5% | Both at same time | 0% |
| Never automates but imports | 8% | Never automates but has affiliates | 1% |
| Never imports but automates | 36% | Never has affiliates, but automates | 62% |
| Never either | 28% | Never either | 36% |
| Panel (b): Automates using robots | | | |
| Importing intensively from less developed countries | | Opening affiliates in less developed countries | |
| Sequencing | Share of firms | Sequencing | Share of firms |
| First automates then imports | 7% | First automates, then opens affiliates | - |
| First imports then automates | 8% | First opens affiliates, then automates | - |
| Both at same time | 2% | Both at same time | 0% |
| Never automates but imports | 20% | Never automates but has affiliates | 3% |
| Never imports but automates | 14% | Never has affiliates, but automates | 27% |
| Never either | 50% | Never either | 70% |

Notes: This table displays the share of firms by their sequencing of automation and importing intensively or opening affiliates in less developed countries. Importing intensively is defined as being in the top 20% of the sample in terms of import intensity from less developed countries.

## 4.3 Which comes first? Automation or importing/opening affiliates

We have shown that firms that automate, on average, import more and have more affiliates in less developed countries, although their import share from less developed countries is lower. We have also shown that importing from less developing countries appears to co-occur with the timing of automation. But it is not yet clear which is causing the other. We hence further consider the timing of when firms automate and when they start importing intensively or opening up affiliates in less developed countries. We define importing intensively from less developed countries as being in the top 20th percentile in terms of the ratio of imports from less developed countries to output. We define automating as using either robots, CNC machines or flexible manufacturing systems.

The debate around 'reshoring' typically assumes that firms first offshored production, then returned it home again. If automation is a cause of reshoring, then we might expect that firms would first report either importing intensively from, or having affiliates in, developing countries, then later report automating, followed by a decline in import intensity or affiliates in less developed countries. Panel (a) of table 5 shows that, in fact, far more firms started automating, using any one of these three technologies, before they started importing intensively. Only 36% of firms ever import intensively from less developed countries, while 64% automate at some point. The most common

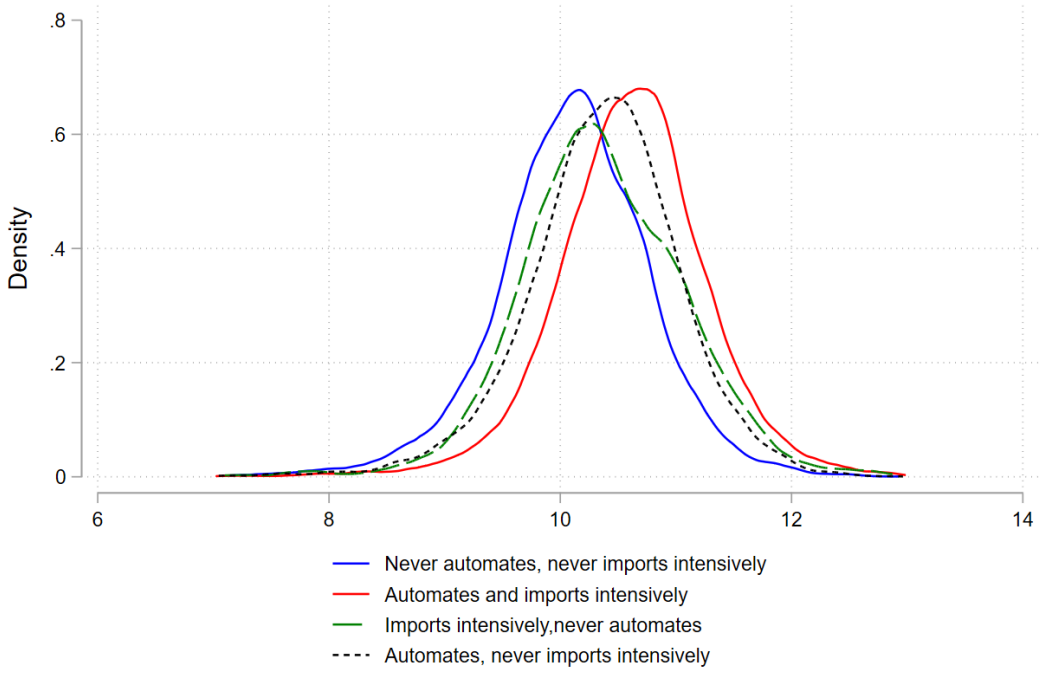
outcome is for firms to automate but never import intensively. Of those that do both, they are more than twice as likely to report automating before they import intensively. Panel (b) focuses on only those that automate using robots, which is a smaller fraction of firms. Only 30% of firms use robots at some point in the sample, and using robots is less common than importing intensively from less developed countries. For firms that do both, they are almost equally likely to be importing intensively before they automate as vice versa.

Having an affiliate in a less developed country is far less common than importing intensively from less developed countries. Only 6% of our sample ever report having affiliates in developing countries. Our variables on affiliates were only introduced after 2000 and so we cannot compare the timing of those that do both, but we show that it is very rare for firms in our sample to report having affiliates in developing countries but never automating. Of those that have affiliates in less developed countries, only 17% never automate using one of the three technologies.

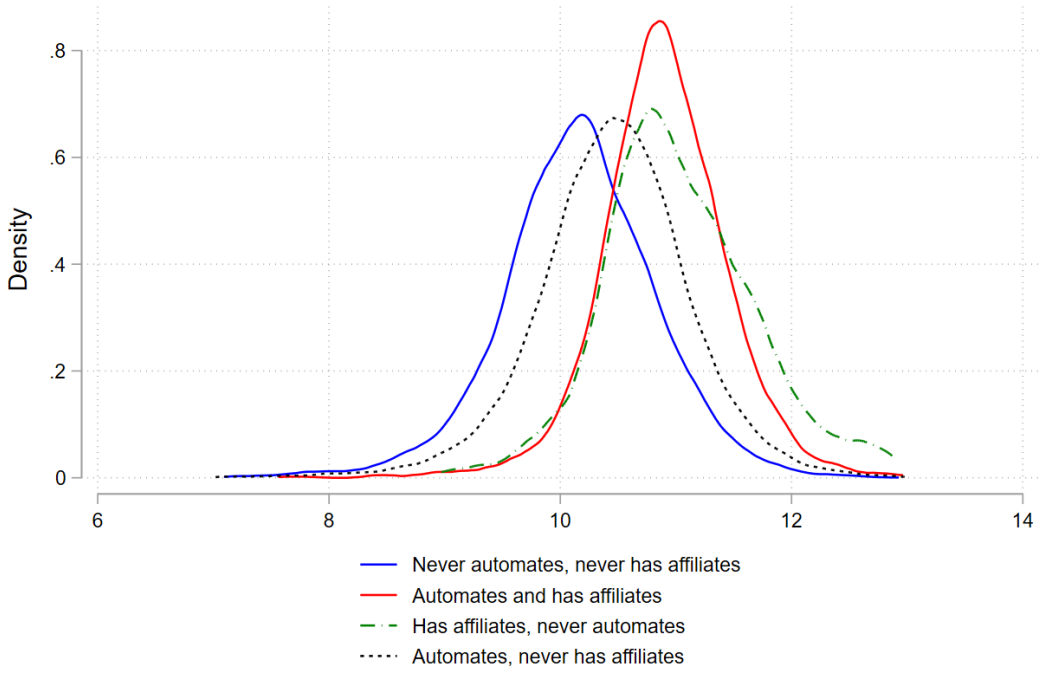
## 4.4 Productivity of firms that automate, import and have affiliates

We assumed in our model section that firms select into automating and offshoring depending on their productivity, with the most productive firms both automating and offshoring and the least productive firms doing neither. We show in Figure 5 that this is the case in our data. We define automating and importing intensively as above. Panel (a) shows that firms that both automate and import intensively have a labour productivity distribution that is a shift right relative to firms that do one or the other, with the distribution of those that do neither the furthest left. The distributions of those that only do one or the other are relatively similar, with the distribution for firms that only automate being just a very slight shift right of that for firms that only import intensively. Panel (b) displays the analogy of this graph for having affiliates in developing countries. Again the distribution of firms that both automate and have affiliates in less developed countries is the furthest right with the distribution for firms that do neither furthest left. However, with affiliates the distribution for firms that only have affiliates and never automate is further right than the distribution for firms that only automate.

Figure 8 in the Appendix also displays the share of firms that do both, do either and do neither by industry. In terms of import intensity the industries with the highest share of firms doing both are 'Computer products, electronics and optical', 'Chemicals and pharmaceuticals', 'Other transport equipment', 'Basic metal products' and 'vehicles and accessories'. In terms of affiliates, three of those are also in the top five for having the highest share of firms do both, with 'Machinery and Equipment'




(a) Importing intensively from less dev. countries




(b) Affiliates in less dev. countries

Figure 5: Labour productivity distribution by automation and importing or MNC status

and 'Beverage' also in the top 5. In terms of import intensity, the industry with the highest share of firms only importing intensively is 'Leather, fur and footwear', followed by 'Textiles and Clothing', as might be expected.

# 5 Empirical strategy

In Section 4 we demonstrated that firms that will select into automation in the future already have distinct characteristics relative to those that never automate and the gap is then wider for firms that have automated. This provides some early indication that automation might have a causal impact on firm outcomes, but could also be driven by differences between firms that automate at different times. In this section we aim to provide further evidence by evaluating the causal impact of automation on our key firm outcomes. The baseline specification we aim to estimate is:

$$\mathrm{X}_{it} = \alpha + \beta \mathrm{Robots}_{it} + \theta \text{industry-year}_{it} + \phi \text{region-year}_{it} + \gamma_i + \epsilon_{it} \tag{21}$$

where $\mathrm{X}_{it}$ is the outcome of interest for firm $i$ in year $t$ , $\mathrm{Robots}_{it}$ is a dummy variable for firm use of robots at time $t$ and $\gamma_i$, $\text{industry-year}_{it}$ and $\text{region-year}_{it}$ are firm, industry-year and region-year fixed effects. By including firm fixed effects our specification estimates the impact of changes in robot use within firms over time. We include industry-year fixed effects in order to pick up any trends that may have differentially affected industries in different time periods. We further include region-year fixed effects in order to control for any policy changes that affected specific regions in specific time periods.

The models in equation 21 can be estimated directly by a panel data fixed effects regression. However, there are a few reasons why the technology use dummy variables could be correlated with the error term, resulting in biased estimates. First, these equations could suffer from reverse causality. In Section 4 we demonstrated that firms that select into automation in the future have different characteristics to firms that do not. Firms that are expanding, reorganising or adjusting their international orientation may adopt technology as a response to these other changes the are undergoing. Second, there could be common shocks that affect both automation and the outcome variables. For example it is plausible that there may be shocks to labour demand or trade that also affect the decision to automate.

In order to isolate the causal impact of automation on firm performance and offshoring, we construct two separate instruments for the adoption of robots. The first follows Webb (2019) and maps robotics patents to occupations conducting similar tasks. We then use the ex-ante 'exposure' of industry-region pairs to advances in robotics over time, based upon their employment composition in the 1980s. The second serves as a robustness check and follows Graetz and Michaels (2018). We outline these two methods below.

## 5.1 Exposure to advances in robotics using patents

One of the best ways of tracking technological progress in automation at its origin is through studying patents. We aim to develop a measure of the raw technological supply side for automation through looking at the stock of robot related patents, linked to the occupations that they potentially replace. Our motivation is that many technological developments stem from research conducted at universities and breakthroughs are often because of advances in complementary technologies in other fields or specific discoveries. For example, industrial robots have typically had limited mobility due to the cost of batteries and sensors. Only recently, cost declines for components such as lidar, which are used as sensors, or small and powerful batteries, have led to advances in mobile robotics. Cost declines for lidar were largely driven by the security industry and battery technology due to smartphones.

For manufacturing firms in Spain, these advances which made it suddenly possible to purchase a good quality robot at a low enough price were largely exogenous to them. Different manufacturing processes also involve different tasks, some of which became possible to automate with robots, while others did not. In the IFR data, most of the robot applications are conducted by a robotic arm, while smaller, intricate processes involving manual dexterity are still relatively hard to automate. These patterns are plausibly exogenous to the firm and particularly to a Spanish firm, given most robotics research and development generally occurs outside of Spain.

This method builds upon these observations and aims to measure the stock of robotics inventions aimed at conducting specific tasks. A detailed summary of the method can be found in Webb (2019), although we differ in this paper by adding a time dimension. The method uses the text of patents to identify the tasks that robots can perform, then quantifies the extent to which each occupation in the economy involves performing similar tasks. A brief summary is as follows:

The first step of this method involved selecting patent publications related to industrial robots from the Google Patents Public Data database using keyword searches of patent titles and abstracts,

and CPC codes. The next step involved extracting verb-noun pairs from the patent titles. This was done use a dependency parsing algorithm (Honnibal and Johnson, 2015) to determine the syntactic relations of the words in the sentence. For each verb, its direct object was identified by the algorithm, if it existed. The verb and noun were then lemmatized, so that, say, "predicting" and "predicted" were both recorded as "predict". Stop words such as "use" and "have", which do not express economic applications, are dropped.

The O*NET database was then used as the source of information on occupations. As noted above, each occupation consists of a collection of tasks described in natural language. The same dependency parsing algorithm was used to extract verb-noun pairs. Before calculating an exposure score for each verb-noun pair, nouns were grouped into conceptual categories. This was done using WordNet (Miller 1995), a database developed at Princeton University that groups nouns into a hierarchy of concepts. For example, the ancestors of "economist" are "social scientist", "scientist", "person", "causal agent", "physical entity", and "entity".

An occupation's final exposure score was then calculated using the set of aggregated verb-noun pairs extracted from its task descriptions and this score expresses the intensity of the stock of patenting activity up until that date directed towards the tasks in that occupation. We then develop an industry-region level measure of 'exposure' using the 1980s occupational composition of employment in a given region and industry and the patent measures for each occupation code. The instrument for robot use by firm $i$ in industry $j$ and region $r$ at time $t$ is then:

$$\text{robot}_{irjt} = \text{exposure}_{rjt}^{robotpatent} \tag{22}$$

where

$$\text{exposure}_{rjt}^{robotpatent} = \sum_{o=1}^{n} \text{automatable}_{ot}^{patent} \times \text{employment}_{orj1980} \tag{23}$$

where $\text{automatable}_{ot}^{patent}$ is the patent measure of automatability for occupation code $o$ in year $t$ and $\text{employment}_{orj1980}$ is the employment share of occupation $o$ in region $r$ and industry $j$ in 1980.

For the specification for robots we estimate 21 in levels with firm fixed effects. Because our instrument is at the industry-region-year level, there is insufficient variation across industries within different regions to include both industry-year and region-year fixed effects and so we aggregate the NACECLIO industries to a higher level industry grouping and include industry group-year fixed effects, along with region-year fixed effects.

### 5.1.1 Insights from exposure measures

**Most and least exposed occupations:** Webb (2019) provides a detailed discussion of the results on the exposure of different occupations. In summary, the most exposed occupations include various kinds of materials movers in factories and warehouses, and tenders of factory equipment. Many of these occupations have in fact seen robot-driven automation. The least-exposed occupations include payroll clerks, artistic performers, and clergy. These do not primarily involve the kinds of repetitive manual tasks that robots automate.

**Most and least exposed industries and regions:** Figure 6 displays the most and least exposed industry-region pairs, using the 1980s employment weighting of the occupational exposure scores. The most exposed industry-region pair is the construction of automobiles and spare parts in Navarra, while the least exposed industry-region pair is Office machines and Computers (including installation) in Canarias. We find that there is substantial variation in the exposure of the same industries in different regions, suggesting that the same industry can have a different occupational composition depending on its location. Figure 9 in the Appendix also documents how these exposure measures vary over time.

## 5.2 Alternative exposure measure using robot sales data

For comparison we also construct an alternative measure for exposure to industrial robots using sales data from the International Federation or Robotics (IFR). The IFR provides global sales and operational stock of industrial robots by 'application'. Examples of the IFR applications are 'metal casting' or 'plastic moulding' or 'arc welding'. In a similar vain to Graetz and Michaels (2018) we hand match robot applications to ISCO 68 occupation codes. We do so as follows: we define a 4 digit occupation code as 'automatable' in a given year using industrial robots if its title or formal description contains any of the words included in the application titles of the IFR data and there is a positive operational stock of that application robot type . We then develop an industry-region level measure of 'exposure' in a similar way to that used for patents by combining the 1980s occupational composition of employment in a region and industry and the classification of occupation codes. As this measure has limited time series variation, we additionally interact the exposure measure with the global operational stock of all industrial robots to obtain a shift share instrument.

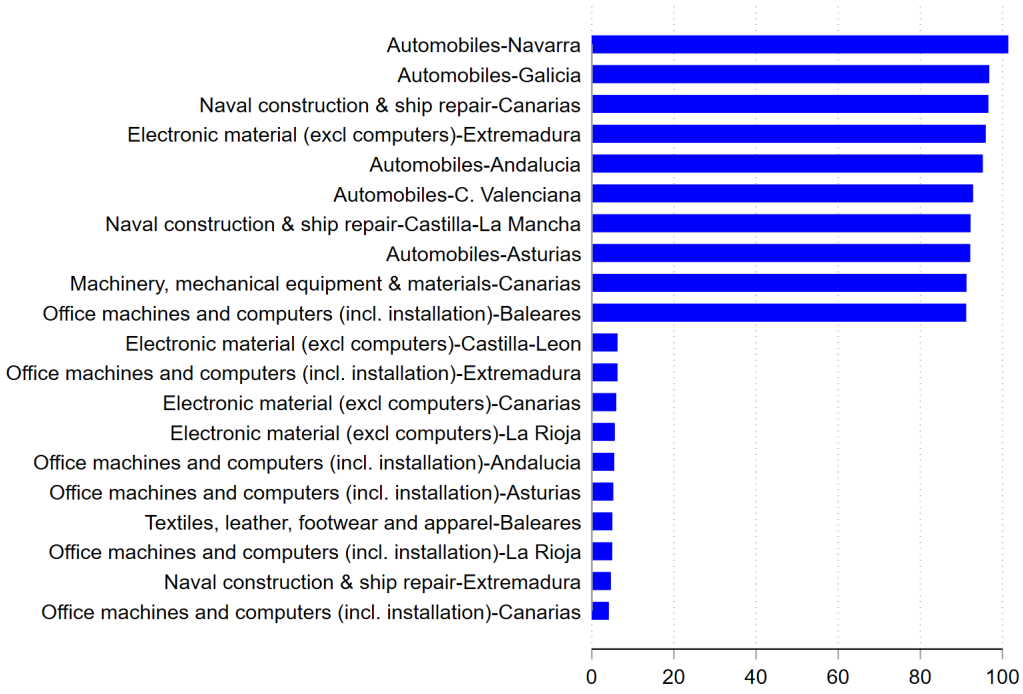



Figure 6: Top 10 industry-region pairs with highest and lowest median exposure scores

*Notes:* This figure displays the activity-region pairs with the highest and lowest median employment-weighted patent robot exposure scores across years.

# 6 Results

## 6.1 Baseline results

Table 6 first presents the baseline results without instrumenting for robot use. We take the IHS transformation of the value of imports, the import intensity and the number of affiliates, due to the prevalence of zeros. We log all other variables except for the shares. We cluster standard errors throughout at the industry-region-year level in light of the sampling design of the ESEE data and our instruments being at this level.[14] Panel (a) displays results for the outcome variables relating to imports and multinational activity involving less developed countries. These results suggest that within-firm switching into using robots is associated with an increase in the value of imports from less developed countries and the intensity of imports from less developed countries, but not with the share of imports from less developed countries or multinational activity in less developed countries. Panel (b) displays the results for the domestic outcome variables. These results suggest that within-firm

[14]We also tried alternative methods for clustering, such as at the firm level, finding this did not change the significance level of any of the coefficients in our baseline regressions.

TABLE 6. RESULTS WITHOUT IV

| | FIXED EFFECTS REGRESSIONS 1990-2016 | | | | |
|---|---|---|---|---|---|
| | Panel (a): International outcomes involving less developed countries | | | | |
| Dep variable: | Imports | Import intensity | Import share | Affiliates | Affiliate share |
| | (1) | (2) | (3) | (4) | (5) |
| Robot use | 0.0021*** | 0.38*** | -0.0036 | -0.0026 | 0.00091 |
| | (0.00070) | (0.083) | (0.0052) | (0.0061) | (0.0029) |
| Observations | 46399 | 46435 | 46435 | 28358 | 28336 |
| Firm FE | Y | Y | Y | Y | Y |
| Region-year FE | Y | Y | Y | Y | Y |
| Industry Group-Year FE | Y | Y | Y | Y | Y |
| | Panel (b): Domestic outcomes | | | | |
| Dep variable: | Employment | Output | Labour share | Labour productivity | TFP |
| | (6) | (7) | (8) | (9) | (10) |
| Robot use | 0.053*** | 0.096*** | -0.0058 | 0.031*** | 0.049*** |
| | (0.0060) | (0.0077) | (0.0036) | (0.0086) | (0.0096) |
| Observations | 44277 | 46220 | 44196 | 43688 | 39184 |
| Firm FE | Y | Y | Y | Y | Y |
| Region-year FE | Y | Y | Y | Y | Y |
| Industry Group-Year FE | Y | Y | Y | Y | Y |

Notes: This table presents estimates of the relationship between the dummy variable for firm use of robots and the dependent variables, listed in columns 1-10. The variables in columns 1,2, and 4 are transformed by IHS, while the variables in columns 6,7, 9 and 10 are logged. These results are not weighted. Standard errors are robust to heteroskedasticity and serial correlation at the industry-region-year level.

switching into using robots is also associated with higher employment, greater production of goods or services, higher labour productivity and higher TFP.

Table 7 next displays the equivalent results now using the patent IV. In all regressions the first stage is strong, demonstrating that the patent exposure measure is a good predictor of whether a firm uses robots. Panel (a) shows the results for the outcome variables relating to trade with less developed countries. Starting to use robots has a substantial positive impact on imports from less developed countries. a positive impact on the intensity of imports from less developed countries and, in contrast to the specification without instrumenting for robots, a positive impact on the number of affiliates in less developed countries. Robot use has no statistically significant effect on the share of imports from less developed countries, however, or on the share of affiliates in less developed countries. Panel (b) displays the results for domestic outcomes. We find that, when using this IV, starting to use robots raises employment, the value of goods and services produced, labour productivity and TFP. In contrast to the results without the IV, robot use also decreases the labour share.

These coefficients imply substantial impacts on robot adoption. The coefficient for imports from less developed countries implies that starting to use robots cases an approximately 13 fold increase in the value of imports. This value accounts for both the extensive margin and intensive margin of trade,

TABLE 7. BASELINE IV RESULTS

| | IV FIXED EFFECTS REGRESSIONS 1990-2016 | | | | |
|---|---|---|---|---|---|
| | Panel (a): International outcomes involving less developed countries | | | | |
| Dep variable: | Imports | Import intensity | Import share | Affiliates | Affiliate share |
| | (1) | (2) | (3) | (4) | (5) |
| Robot use | 12.8*** | 0.050* | -0.14 | 0.49** | 0.12 |
| | (3.25) | (0.027) | (0.16) | (0.25) | (0.11) |
| First stage coef. | 0.0049*** | 0.0049*** | 0.0049*** | 0.0041*** | 0.0041*** |
| | (0.00076) | (0.00076) | (0.00076) | (0.00100) | (0.00100) |
| First stage F stat | 40.5 | 40.5 | 40.5 | 17.1 | 17.1 |
| Observations | 37517 | 37488 | 37517 | 23067 | 23045 |
| Firm FE | Y | Y | Y | Y | Y |
| Region-year FE | Y | Y | Y | Y | Y |
| Industry Group-Year FE | Y | Y | Y | Y | Y |
| | Panel (b): Domestic outcomes | | | | |
| Dep variable: | Employment | Output | Labour share | Labour productivity | TFP |
| | (6) | (7) | (8) | (9) | (10) |
| Robot use | 0.60** | 2.49*** | -0.49*** | 1.51*** | 3.06*** |
| | (0.27) | (0.45) | (0.11) | (0.33) | (0.53) |
| First stage coef. | 0.0048*** | 0.0049*** | 0.0048*** | 0.0047*** | 0.0053*** |
| | (0.00079) | (0.00077) | (0.00080) | (0.00080) | (0.00085) |
| First stage F stat | 36.5 | 40.2 | 35.8 | 34.9 | 39.1 |
| Observations | 35910 | 37371 | 35845 | 35523 | 32025 |
| Firm FE | Y | Y | Y | Y | Y |
| Region-year FE | Y | Y | Y | Y | Y |
| Industry Group-Year FE | Y | Y | Y | Y | Y |

Notes: This table presents estimates of the relationship between the dummy variable for firm use of robots and the dependent variables, listed in the columns 1-10. The variables in columns 6, 7, 8 and 9 are logged, while the variables in columns 1,2 and 4 are transformed by IHS. The instrument used is the patent derived measure of industry-region-year exposure to robots. These results are not weighted. Standard errors are robust to heteroskedasticity and serial correlation at the industry-region-year level.

which offers one explanation for why the impact is so large, as will be discussed in the next section. We also try replacing the IHS transformation with alternatives in the Robustness section, demonstrating that this result still holds when we do so. The coefficient for import intensity implies that starting to use robots causes approximately a 5% increase in the value of imports relative to output, although this result is only weakly significant. The coefficient for affiliates implies that starting to use robots causes firms to increase their number of affiliates in less developed countries by approximately 50%.

The effect of robot use on domestic outcomes is also substantial. These results imply that within-firm switches to using robots increase employment in the firm in Spain by around 60%, cause a more than twofold increase in output, decrease the labour share of income by 0.49, more than double labour productivity and cause a more than threefold increase in TFP.

## 6.2 Extensive margin and changes to employment and activities at affiliates

We next explore how robot use affects the extensive margin of importing from, or opening affiliates in, less developed countries. Our results above in Table 7 demonstrated that there was a very high coefficient for the impact of robot use on the value of imports, which could be driven by firms switching into importing from developing countries as well as the value of imports conditional on importing. Table 8 first displays results for the impact of robot use on a dummy variable for whether a firm imports from less developed countries, in Column (1) and whether it has affiliates in less developed countries in Column (2). For importing, the coefficient is statistically significant to the 5% level, showing that within-firm switching into using robots has a positive impact on whether a firm imports from less developed countries. Starting to use robots makes firms 57% more likely to import from less developed countries. For opening affiliates, the coefficient is statistically significant to the 10% level, showing a weak relationship between using robots and opening affiliates in less developed countries.

Columns 3-6 display outcomes at the firm's main foreign affiliate. Starting to use robots also increases employment at the firm's main affiliate quite substantially. In terms of the primary activity conducted at the main affiliate, we find a positive impact of robot use on firms starting to report that 'the activity of the affiliated company consists only in commercialization or distribution' or that 'the main affiliated company manufactures similar products to those manufactured in Spain by its company', while there is no impact on reporting that 'the main affiliated company carries out

TABLE 8. EXTENSIVE MARGIN AND AFFILIATE ACTIVITIES

| | IV FIXED EFFECTS REGRESSIONS 1990-2016 | | | | | |
|---|---|---|---|---|---|---|
| | Extensive margin | | Activities at main affiliate | | | |
| Dep variable: | Stars importing | Opens affiliates | Affiliate employment | Adaptation & assembly | Marketing & distribution | Similar production |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Robot use | 0.57** | 0.30* | 2.77** | 0.12 | 0.35** | 0.42** |
| | (0.24) | (0.16) | (1.09) | (0.11) | (0.16) | (0.18) |
| First stage F stat | 40.5 | 17.1 | 16.9 | 17.1 | 17.1 | 17.1 |
| Observations | 37517 | 23067 | 22631 | 23044 | 23044 | 23044 |
| Firm FE | Y | Y | Y | Y | Y | Y |
| Region-year FE | Y | Y | Y | Y | Y | Y |
| Industry Group-Year FE | Y | Y | Y | Y | Y | Y |

Notes: This table presents estimates of the relationship between the dummy variable for firm use of robots and the dependent variables, listed in the columns 1-10. All variables are dummy variables except for the affiliate employment variable, which is transformed by IHS. The instrument used is the patent derived measure of industry-region-year level exposure to robots. These results are not weighted. Standard errors are robust to heteroskedasticity and serial correlation at the industry-region-year level.

adaptation and/or assembly activities of parts provided by the company in Spain'. These results suggest that the increase in multinational activity is concentrated in horizontal, rather than vertical FDI, where horizontal is associated with duplicating similar production stages across countries, while vertical reflects locating different production stages in different countries. These results provide some suggestion that it is plausible that as firms start to automate, they still expand abroad, but their focus shifts away from labour cost differentials and more towards market expansion.

## 6.3 Sequencing of automation and importing intensively

Our model predicted that in light of the fixed costs involved with automating or offshoring, the sequencing of these decisions would matter for the impact of automation. If a firm offshored first, we would expect that the displacement effect would occur for offshore labour, as well as domestic labour, dampening the impact on domestic labour. If a firm had not offshored first, we would not expect a displacement effect for current offshore labour. In Table 9 we display our baseline results firstly restricting the sample to only firms that started importing intensively from less developed countries prior to using robots and then using the full sample with interaction terms. As in section 4, we define importing intensively from less developed countries as being in the top 20% of the sample in terms of imports from less developed countries, equivalent to importing 1% of more of total output. Given that multinational activity variables only start from 2000, limiting the sample this way is not feasible for multinational activity and so we focus on importing variables only.

Panel (a) displays the results for the limited sample. Focusing only on firms that started importing intensively from less developed countries first yields quite different results to those for the full sample. For this group, starting to use robots has no effect on the value of imports from less developed countries, the import intensity or on the extensive margin. Its only effect is to reduce

TABLE 9. SEQUENCING OF IMPORTING INTENSIVELY AND AUTOMATION

| | IV FIXED EFFECTS REGRESSIONS 1990-2016 | | | |
|---|---|---|---|---|
| | Panel (a): Only firms that import intensively first | | | |
| Dep variable: | Imports | Import intensity | Import share | Starts importing |
| | (1) | (2) | (3) | (4) |
| Robot use | 0.49 | 0.037 | -0.39** | -0.26 |
| | (3.17) | (0.051) | (0.20) | (0.25) |
| First stage F stat | 29.5 | 29.3 | 27.3 | 27.3 |
| Observations | 5612 | 5602 | 5665 | 5665 |
| Firm FE | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y |
| Region-year FE | N | N | N | N |
| Industry Group-Year FE | N | N | N | N |
| | Panel (B): Full sample with first importing intensively interaction | | | |
| Dep variable: | Imports | Import intensity | Import share | Starts importing |
| | (5) | (6) | (7) | (8) |
| Robot use | 16.0*** | 0.051 | -0.18 | 0.76** |
| | (4.05) | (0.033) | (0.21) | (0.31) |
| Robot * first import intensively | -14.3*** | -0.0085 | 0.16 | -0.76*** |
| | (3.62) | (0.028) | (0.18) | (0.27) |
| First stage F stat | 18.5 | 18.4 | 17.7 | 17.7 |
| Observations | 37285 | 37256 | 37517 | 37517 |
| Firm FE | Y | Y | Y | Y |
| Region-year FE | Y | Y | Y | Y |
| Industry Group-Year FE | Y | Y | Y | Y |

Notes: This table presents estimates of the relationship between the dummy variable for firm use of robots and the dependent variables, listed in the columns 1-8. The value of imports and import intensity are transformed by IHS. The instrument used is the patent derived measure of industry-region-year level exposure to robots. These results are not weighted. Standard errors are robust to heteroskedasticity and serial correlation at the industry-region-year level.

the share of imports from less developed countries by 0.39. These results suggest that firms that were already importing intensively, upon adopting robots, do not change their imports from less developed countries, but start importing from high-income countries, meaning the less developed country share of imports declines. Panel (b) displays the results when including the full sample but using interaction terms for the differential impact of being a firm that imported intensively first on the outcome variables. For the value of imports, the coefficient on the interaction term for firms that imported intensively first is negative and significant, suggesting that there is a statistically significant difference between the impact of robots on imports from less developed countries depending on the sequencing of importing and automating. The same applies for the extensive margin. For the other two variables, however the difference is not statistically significant. These results generally support our model prediction that the sequencing of these decisions matters for their impact.

TABLE 10. CHANGES TO EMPLOYMENT AND OPERATIONS IN SPAIN

| | IV FIXED EFFECTS REGRESSIONS 1990-2016 | | | | | |
|---|---|---|---|---|---|---|
| Dep variable: | Labour Costs | Change regular workers | Production | Administrative | Nongraduates | Engineers & graduates |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Robot use | 0.62** | 0.44** | 0.80** | -0.14 | 0.33 | 1.13*** |
| | (0.27) | (0.19) | (0.31) | (0.35) | (0.37) | (0.41) |
| First stage F stat | 36.0 | 40.7 | 36.7 | 36.7 | 35.1 | 36.3 |
| Observations | 35938 | 33124 | 35898 | 35898 | 35699 | 35719 |
| Firm FE | Y | Y | Y | Y | Y | Y |
| Region-year FE | Y | Y | Y | Y | Y | Y |
| Industry Group-Year FE | Y | Y | Y | Y | Y | Y |

Notes: This table presents estimates of the relationship between the dummy variable for firm use of robots and the dependent variables, listed in the columns 1-6. The labour costs variable is logged, while the variables in columns 3-6 are transformed by IHS. The instrument used is the patent derived measure of industry-region-year level exposure to robots. These results are not weighted. Standard errors are robust to heteroskedasticity and serial correlation at the industry-region-year level.

## 6.4 Changes to employment in Spain

We next delve into the details of what was happening in terms of employment within the firms in Spain. Our results in Table 7 showed a strong positive impact of robot use on output, a strong negative impact on the labour share and a weak positive impact on employment in Spain. These results suggest that the impact on the labour share is not through decreased employment but through total income increasing relatively more than labour costs. We begin by picking apart this result for the labour share by additionally looking at how robot use affected total labour costs. Column 1 in Table 10 shows that the impact on labour costs was similar to the impact on employment.

Our model predicted that automation has both a productivity effect, whereby firms that automate can benefit from lower marginal costs, increase productivity and expand, and a displacement effect whereby a subset of tasks are automated. This would suggest that we should see the reorganisation of production within firms in Spain as some tasks and displaced and the composition of employment shifts to the tasks that are not feasible to automate. The ESEE data asks firms whether 'during the financial year, there has been a significant change in the number of regular workers', allowing us to evaluate if automation does lead to this composition shift. Column 2 shows that starting to use robots does indeed have an impact on the changing of regular workers, with robot use leading firms to be 44% more likely to report a change. Columns 3-6 explore the impact on different types of employment. The category that is most affected is the number of engineers or graduates, which are more than doubled as a consequence of adopting robots and production workers, which are increased by 80%. Meanwhile we find no effect of robot use on the number of administrative workers or non-graduates.

TABLE 11. INTENSIVE MARGIN OF AUTOMATION

| | IV FIXED EFFECTS REGRESSIONS 1990-2016 | | | | |
|---|---|---|---|---|---|
| | Panel (a): International outcomes involving less developed countries | | | | |
| Dep variable: | Imports (1) | Import intensity (2) | Import share (3) | Affiliates (4) | Affiliate share (5) |
| Log machinery stock | 0.73*** | 0.0031** | -0.00024 | 0.034** | 0.0082 |
| | (0.17) | (0.0015) | (0.0093) | (0.017) | (0.0071) |
| First stage coef. | 0.091*** | 0.091*** | 0.088*** | 0.064*** | 0.064*** |
| | (0.013) | (0.013) | (0.013) | (0.016) | (0.016) |
| First stage F stat | 52.5 | 52.7 | 49.5 | 16.0 | 16.0 |
| Observations | 35216 | 35195 | 35435 | 22119 | 22097 |
| Firm FE | Y | Y | Y | Y | Y |
| Region-year FE | Y | Y | Y | Y | Y |
| Industry Group-Year FE | Y | Y | Y | Y | Y |
| | Panel (b): Domestic outcomes | | | | |
| Dep variable: | Employment (6) | Output (7) | Labour share (8) | Labour productivity (9) | TFP (10) |
| Log machinery stock | 0.027* | 0.13*** | -0.030*** | 0.089*** | 0.19*** |
| | (0.016) | (0.024) | (0.0061) | (0.019) | (0.034) |
| First stage coef. | 0.085*** | 0.088*** | 0.085*** | 0.082*** | 0.087*** |
| | (0.013) | (0.013) | (0.013) | (0.013) | (0.014) |
| First stage F stat | 43.3 | 49.2 | 43.6 | 40.6 | 38.8 |
| Observations | 34185 | 35336 | 34146 | 33846 | 30716 |
| Firm FE | Y | Y | Y | Y | Y |
| Region-year FE | Y | Y | Y | Y | Y |
| Industry Group-Year FE | Y | Y | Y | Y | Y |

Notes: This table presents estimates of the relationship between the interaction term for the dummy variable for firm use of robots × the log of the stock of investment in industrial machinery and equipment and the dependent variables, listed in the columns 1-10. The variables in columns 1,2 and 4 are transformed by IHS, while the variables in columns 6, 7, 9 and 10 are logged. The instrument used is the patent derived measure of industry-region-year level exposure to robots. These results are not weighted. Standard errors are robust to heteroskedasticity and serial correlation at the industry-region-year level.

## 6.5 Intensive margin of automation

So far our results have focused on the extensive margin of robot use using the dummy variable for whether firms use robots or not. It is also interesting to consider how the intensive margin of the extent of robot use affects our outcome variables. Our dataset does not include the total number of robots used, but does provide one variable of relevance: the share of annual investment that is in the 'purchase of technical facilities, machinery and tools'. Combined with annual total investment and the average depreciation rate, we use this variable to construct a measure of the annual stock of technical facilities, machinery and tools, using the perpetual inventory method. We then interact this variable with the robot dummy variable to obtain a proxy for the stock of industrial machinery for firms using robots.

Table 11 shows the results using this intensive margin robot stock variable as the independent variable. Although the coefficient magnitudes now have a different interpretation, the results are

qualitatively similar. An increase in the stock of industrial machinery has a positive impact on the value of imports from less developed countries, the intensity of imports from less developed countries and the number of affiliates in less developed countries. In terms of magnitude, a 10% increase in the stock of industrial machinery for robot users increases imports from less developed countries by around 7%, the intensity of imports from less developed countries by around 0.03% and the number of affiliates in less developed countries by around 3%. For domestic outcomes the results are also qualitatively similar for the intensive margin: the intensity of use of industrial machinery for robot users very weakly raises employment and strongly raises output, labour productivity and TFP, while decreasing the labour share.

# 7 Robustness

## 7.1 Controlling for import tariff changes

Our instrument relies on both cross-sectional variation in industry-region level occupational employment shares in 1981 and on time series variation in occupation-specific patenting activity. One concern is that changes in patenting activity could be correlated with other time-varying shocks that may have affected importing or multinational activity with developing countries. In order to counteract this possibility, we include both industry group-year and region-year fixed effects. However, we are not able to include industry-year fixed effects because this reduces the variation in our instrument too much. There is therefore the possibility that there could be time-varying shocks to industries within the same industry group, within regions, and, if these were correlated with our outcome variables we would incorrectly attribute the effect to automation.

In the context of offshoring, one change we might be particularly concerned about is the fall in import tariffs that may have reduced the cost of offshoring to less developed countries, for example China. In this section we therefore include additional controls for industry level import tariffs. We do so by following the method of Chen and Steinwender (2019). Import tariffs for Spain are set at the EU level and are hence plausibly exogenous to Spanish firms. We construct two control variables: one for MFN import tariffs on the intermediate inputs of an industry, which we denote as 'imported input tariffs', and the other for MFN import tariffs on products in the same industry, which we denote as 'same-industry import tariffs'. The construction of these variables was outlined in the Data section.

The baseline results adding these additional controls are displayed in Table 12. Adding these

TABLE 12. CONTROLLING FOR IMPORT TARIFF CHANGES

| | IV FIXED EFFECTS REGRESSIONS 1990-2016 | | | | |
|---|---|---|---|---|---|
| | Panel (a): International outcomes involving less developed countries | | | | |
| Dep variable: | Imports (1) | Import intensity (2) | Import share (3) | Affiliates (4) | Affiliate share (5) |
| Robot use | 12.7*** | 0.050** | -0.17 | 0.50** | 0.12 |
| | (2.99) | (0.025) | (0.16) | (0.24) | (0.10) |
| Log imported input tariffs | -0.079 | -0.00037 | -0.024 | -0.0015 | -0.00061 |
| | (0.29) | (0.0020) | (0.015) | (0.019) | (0.0092) |
| Log same industry import tariffs | 0.73*** | 0.0047*** | 0.037*** | 0.0070 | -0.00038 |
| | (0.22) | (0.0014) | (0.011) | (0.014) | (0.0060) |
| First stage F stat | 46.9 | 46.9 | 43.8 | 18.4 | 18.4 |
| Observations | 37241 | 37212 | 37473 | 23023 | 23001 |
| Firm FE | Y | Y | Y | Y | Y |
| Region-year FE | Y | Y | Y | Y | Y |
| Industry Group-Year FE | Y | Y | Y | Y | Y |
| | Panel (b): Domestic outcomes | | | | |
| Dep variable: | Employment (1) | Output (2) | Labour share (3) | Labour productivity (4) | TFP (5) |
| Robot use | 0.63** | 2.45*** | -0.49*** | 1.48*** | 3.02*** |
| | (0.26) | (0.43) | (0.11) | (0.32) | (0.51) |
| Log imported input tariffs | 0.021 | -0.048 | 0.0069 | -0.046 | -0.060 |
| | (0.021) | (0.045) | (0.011) | (0.032) | (0.058) |
| Log same-industry import tariffs | 0.0022 | 0.050 | -0.0071 | 0.037 | 0.056 |
| | (0.015) | (0.033) | (0.0075) | (0.024) | (0.040) |
| First stage F stat | 39.7 | 43.4 | 39.0 | 37.9 | 42.0 |
| Observations | 35866 | 37327 | 35801 | 35479 | 31981 |
| Firm FE | Y | Y | Y | Y | Y |
| Region-year FE | Y | Y | Y | Y | Y |
| Industry Group-Year FE | Y | Y | Y | Y | Y |

Notes: This table presents estimates of the relationship between the dummy variable for firm use of robots and the dependent variables, listed in the columns 1-10. The variables in columns 6, 7, 8 and 9 are logged, while the variables in columns 1,2 and 4 are transformed by IHS. The instrument used is the patent derived measure of industry-region-year level exposure to robots. The import tariff controls are the log of the trade-weighted average intermediate import and import tariffs. These results are not weighted. Standard errors are robust to heteroskedasticity and serial correlation at the industry-region-year level.

controls does not change our coefficients significantly. We find that, somewhat surprisingly, the intermediate input tariffs do not have a statistically significant effect on any of the outcome variables, while import protecting tariffs only have an impact on the import variables.

## 7.2 Weighted results

We also repeat our main results with weightings by baseline firm output. Table 13 displays these results. Weighting the observations does not qualitatively change our conclusions, except for employment, which no longer has a statistically significant coefficient. The remaining coefficients are all, in fact, larger in magnitude with weightings included.

TABLE 13. BASELINE IV RESULTS: WEIGHTED

| | IV FIXED EFFECTS REGRESSIONS 1990-2016 | | | | |
|---|---|---|---|---|---|
| | Panel (a): International outcomes involving less developed countries | | | | |
| Dep variable: | Imports (1) | Import intensity (2) | Import share (3) | Affiliates (4) | Affiliate share (5) |
| Robot use | 16.5*** | 0.062** | -0.15 | 0.69* | 0.19 |
| | (4.25) | (0.031) | (0.18) | (0.35) | (0.14) |
| First stage F stat | 30.7 | 30.8 | 30.7 | 11.5 | 11.5 |
| Observations | 37504 | 37481 | 37504 | 23064 | 23042 |
| Firm FE | Y | Y | Y | Y | Y |
| Region-year FE | Y | Y | Y | Y | Y |
| Industry Group-Year FE | Y | Y | Y | Y | Y |
| | Panel (b): Domestic outcomes | | | | |
| Dep variable: | Employment (6) | Output (7) | Labour share (8) | Labour productivity (9) | TFP (10) |
| Robot use | 0.41 | 2.53*** | -0.55*** | 1.72*** | 3.32*** |
| | (0.31) | (0.52) | (0.13) | (0.41) | (0.64) |
| First stage F stat | 27.2 | 30.9 | 27.2 | 26.4 | 30.5 |
| Observations | 35898 | 37371 | 35845 | 35523 | 32025 |
| Firm FE | Y | Y | Y | Y | Y |
| Region-year FE | Y | Y | Y | Y | Y |
| Industry Group-Year FE | Y | Y | Y | Y | Y |

Notes: This table presents estimates of the relationship between the dummy variable for firm use of robots and the dependent variables, listed in the columns 1-10. The variables in columns 6, 7, 8 and 9 are logged, while the variables in columns 1,2 and 4 are transformed by IHS. The instrument used is the patent derived measure of industry-region-year level exposure to robots. These results are weighted by baseline firm output. Standard errors are robust to heteroskedasticity and serial correlation at the industry-region-year level.

## 7.3 Excluding the Financial Crisis

The Global Financial Crisis fell within the time period of our analysis and so an additional concern is that this may have affected our results. We hence also repeat our analysis excluding the years from 2007-10. Table 14 repeats the analysis in Table 7 for the time period of only 1990-2006 & 2011-2016. The results change slightly but the only qualitative difference is that the coefficient on the import intensity variable is now not statistically significant.

## 7.4 Alternative instrument using IFR data

Table 15 displays the results for the full time period repeated using the IFR exposure measure instead of the patent measure. The first stage coefficient and F stat demonstrate that this instrument is also a strong predictor of robot use. The results are qualitatively similar, with the main difference being that the coefficients on domestic employment and the labour share are now not statistically significant, suggesting that these results are less robust than for the other outcome variables. The coefficient for the value of imports from less developed countries is now slightly less statistically significant at only

TABLE 14. EXCLUDING THE FINANCIAL CRISIS

| | IV FIXED EFFECTS REGRESSIONS 1990-2016 EXCLUDING 2007-2010 | | | | |
|---|---|---|---|---|---|
| | Panel (a): International outcomes involving less developed countries | | | | |
| Dep variable: | Imports (1) | Import intensity (2) | Import share (3) | Affiliates (4) | Affiliate share (5) |
| Robot use | 12.0*** | 0.037 | -0.061 | 0.51* | 0.040 |
| | (3.59) | (0.029) | (0.18) | (0.26) | (0.11) |
| First stage F stat | 33.8 | 33.8 | 33.8 | 17.0 | 17.0 |
| Observations | 31378 | 31349 | 31378 | 16918 | 16896 |
| Firm FE | Y | Y | Y | Y | Y |
| Region-year FE | Y | Y | Y | Y | Y |
| Industry Group-Year FE | Y | Y | Y | Y | Y |
| | Panel (b): Domestic outcomes | | | | |
| Dep variable: | Employment (6) | Output (7) | Labour share (8) | Labour productivity (9) | TFP (10) |
| Robot use | 0.60* | 2.67*** | -0.52*** | 1.76*** | 3.20*** |
| | (0.32) | (0.54) | (0.12) | (0.39) | (0.60) |
| First stage F stat | 30.6 | 33.5 | 29.9 | 29.3 | 34.7 |
| Observations | 29771 | 31232 | 29706 | 29425 | 25998 |
| Firm FE | Y | Y | Y | Y | Y |
| Region-year FE | Y | Y | Y | Y | Y |
| Industry Group-Year FE | Y | Y | Y | Y | Y |

Notes: This table presents estimates of the relationship between the dummy variable for firm use of robots and the dependent variables, listed in the columns 1-10. The variables in columns 1,2 and 4 are transformed by IHS, while the variables in columns 6,7, 9 and 10 are logged. The instrument used is the patent derived measure of industry-region-year level exposure to industrial robots. These results are not weighted. Standard errors are robust to heteroskedasticity and serial correlation at the industry-region-year level.

the 5% level and with a lower magnitude. The coefficients on output, labour productivity and TFP remain statistically significant at 1% but now have lower coefficients. Taken together these results generally suggest that the key results for the impact of robot use on imports from less developed countries, output, labour productivity and TFP are all robust to using an alternative IV for robot use.

## 7.5 Is this just the automotive sector?

The industry in our dataset with the highest prevalence of robot use is Vehicles and Accessories, with 62% of firm-year observations reporting that they use robots, relative to the mean for the full sample of 27%. An additional concern is that our results are driven solely by this one outlier industry, that is particularly reliant on robots for production. We hence also try removing this sector from our analysis. Table 16 displays the results. We find that when we exclude this sector, the impact of robot use on developing country imports remains statistically significant and the coefficient large in magnitude, but the significance and magnitude are somewhat lower than when autos are included. For domestic outcomes, on the other hand, the coefficients are all larger in magnitude and with a

TABLE 15. IFR INSTRUMENT FOR ROBOT ADOPTION

| | IV FIXED EFFECTS REGRESSIONS 1990-2016 | | | | |
|---|---|---|---|---|---|
| | Panel (a): International outcomes involving less developed countries | | | | |
| Dep variable: | Imports | Import intensity | Import share | Affiliates | Affiliate share |
| | (1) | (2) | (3) | (4) | (5) |
| Robot use | 5.69** | 0.048** | 0.15 | 0.42* | 0.028 |
| | (2.23) | (0.020) | (0.17) | (0.23) | (0.10) |
| First stage coef. | 0.021*** | 0.021*** | 0.021*** | 0.021*** | 0.021*** |
| | (0.0030) | (0.0030) | (0.0030) | (0.0030) | (0.0030) |
| First stage F stat | 51.8 | 51.2 | 51.8 | 16.2 | 16.2 |
| Observations | 40557 | 40530 | 40557 | 28358 | 28336 |
| Firm FE | Y | Y | Y | Y | Y |
| Region-year FE | Y | Y | Y | Y | Y |
| Industry Group-Year FE | Y | Y | Y | Y | Y |
| | Panel (b): Domestic outcomes | | | | |
| Dep variable: | Employment | Output | Labour share | Labour productivity | TFP |
| | (6) | (7) | (8) | (9) | (10) |
| Robot use | 0.10 | 1.58*** | -0.067 | 1.18*** | 1.73*** |
| | (0.21) | (0.33) | (0.22) | (0.28) | (0.36) |
| First stage coef. | 0.021*** | 0.021*** | 0.021*** | 0.021*** | 0.021*** |
| | (0.0030) | (0.0030) | (0.0030) | (0.0030) | (0.0030) |
| First stage F stat | 51.5 | 49.7 | 49.7 | 47.2 | 48.0 |
| Observations | 40454 | 40422 | 40419 | 39992 | 39184 |
| Firm FE | Y | Y | Y | Y | Y |
| Region-year FE | Y | Y | Y | Y | Y |
| Industry Group-Year FE | Y | Y | Y | Y | Y |

Notes: This table presents estimates of the relationship between the dummy variable for firm use of robots and the dependent variables, listed in the columns 1-10. The variables in columns 1,2 and 4 are transformed by IHS, while the variables in columns 6,7, 9 and 10 are logged. The instrument used is the patent derived measure of industry-region-year level exposure to industrial robots. These results are not weighted. Standard errors are robust to heteroskedasticity and serial correlation at the industry-region-year level.

TABLE 16. EXCLUDING THE AUTOMOTIVE SECTOR

| | IV FIXED EFFECTS REGRESSIONS 1990-2016 | | | | |
|---|---|---|---|---|---|
| | Panel (a): International outcomes involving less developed countries | | | | |
| Dep variable: | Imports (1) | Import intensity (2) | Import share (3) | Affiliates (4) | Affiliate share (5) |
| Robot use | 8.76** | 0.062* | -0.095 | 0.59* | 0.062 |
| | (3.47) | (0.033) | (0.22) | (0.31) | (0.12) |
| First stage F stat | 26.9 | 26.8 | 24.7 | 13.9 | 13.9 |
| Observations | 35432 | 35403 | 35653 | 21858 | 21836 |
| Firm FE | Y | Y | Y | Y | Y |
| Region-year FE | Y | Y | Y | Y | Y |
| Industry Group-Year FE | Y | Y | Y | Y | Y |
| | Panel (b): Domestic outcomes | | | | |
| Dep variable: | Employment (6) | Output (7) | Labour share (8) | Labour productivity (9) | TFP (10) |
| Robot use | 1.55*** | 4.22*** | -0.70*** | 1.90*** | 4.20*** |
| | (0.37) | (0.85) | (0.18) | (0.49) | (0.90) |
| First stage F stat | 22.9 | 24.3 | 22.3 | 23.0 | 23.7 |
| Observations | 34117 | 35512 | 34053 | 33748 | 30443 |
| Firm FE | Y | Y | Y | Y | Y |
| Region-year FE | Y | Y | Y | Y | Y |
| Industry Group-Year FE | Y | Y | Y | Y | Y |

Notes: This table presents estimates of the relationship between the dummy variable for firm use of robots and the dependent variables, listed in the columns 1-10. The variables in columns 1,2 and 4 are transformed by IHS, while the variables in columns 6,7, 9 and 10 are transformed by the Inverse-Hyperbolic Sine (IHS) transformation. The instrument used is the patent derived measure of industry-region-year level exposure to industrial robots. These results are not weighted. Standard errors are robust to heteroskedasticity and serial correlation at the industry-region-year level.

qualitatively different result for employment, which is now strongly significant and with a magnitude over twice as large. These results generally suggest that for industries other than autos, the impact of robots on domestic outcomes is greater, but the impact on international outcomes weaker, perhaps reflecting the relatively high international orientation of the auto industry.

## 7.6 Alternative specifications for value of imports

We noted in our baseline results table that the coefficient for the value of imports from less developed countries was very high and the estimation problem of having many firm-year observations with zero imports from less developed countries. We hence also try repeating the analysis for this outcome variable including different fixed effects as controls and replacing the IHS transformation with $\log(1+x)$ and a PPML model. For the PPML model, given we have an IV specification we use the control function approach to estimate the second stage and then bootstrap the standard errors to adjust for having included a derived regressor. Table 17 displays the results. We find that trying these alternative

TABLE 17. ALTERNATIVE SPECIFICATIONS FOR IMPORTS REGRESSIONS

| | IV FIXED EFFECTS REGRESSIONS 1990-2016 | | | | |
|---|---|---|---|---|---|
| Dep variable: | Imports from less developed countries | | | | |
| Specification: | IHS (1) | IHS (2) | ln(1+x) (3) | ln(1+x) (4) | PPML (5) |
| Robot use | 12.4*** | 12.3*** | 11.9*** | 11.9*** | 11.6** |
| | (3.09) | (3.29) | (2.95) | (3.14) | (4.86) |
| First stage F stat | 43.5 | 46.9 | 43.5 | 46.9 | - |
| Observations | 37285 | 37285 | 37285 | 37285 | 21342 |
| Firm FE | Y | Y | Y | Y | Y |
| Region-year FE | Y | N | Y | N | Y |
| Industry Group-Year FE | Y | N | Y | N | Y |

Notes: This table presents estimates of the relationship between the dummy variable for firm use of robots and the value of imports from less developed countries, with the specifications in columns 1-5. The instrument used is the patent derived measure of industry-region-year level exposure to industrial robots. These results are not weighted. Standard errors for columns 1-4 are robust to heteroskedasticity and serial correlation at the industry-region-year level. For column 5 we use the control-function method to estimate the IV-PPML model and bootstrap the standard errors.

specifications does not change the magnitude of the coefficient substantially. The specification with the lowest magnitude coefficient is the PPML model, suggesting that there are some signs that selection into importing from less developed countries is inflating our coefficients, although the coefficient still remains very high in magnitude at 11.6. Taken together, these results seem to suggest that robot use has an economically meaningful impact on imports from less developed countries irrespective of the specification we use.

# 8 Conclusion

In this paper we take advantage of a rich dataset of Spanish manufacturing firms between 1990 and 2016 to shed new light on the consequences of automation in a high-income country for imports and multinational activity involving less developed countries. In order to evaluate the causal impact of automation on trade and multinational activity, we exploit supply-side advances in the capabilities of robots over time that made it technically feasible to automate specific tasks. We follow Webb (2019) and use the text from patent titles to identify the tasks that robot-related patents substitute for, mapped to the occupations frequently conducting those tasks. This allows us to construct time-varying measures of exposure to automation with robots.

Using this instrument, we show that starting to use robots in Spain caused a within-firm increase in the value of imports from, and the number of affiliates in, less developed countries. Robot use

also had a positive impact on the extensive margin of trade and multinational activity, leading firms to start importing from, or start opening affiliates in, less developed countries. For multinational activity, the expansion appears to be more directed at horizontal, rather than vertical FDI, however, with robot use increasing the probability that the primary activity of the main affiliate is marketing or distribution of products manufactured in Spain, or producing similar products to those manufactured in Spain, as opposed to assembly or adaptation of inputs supplied by the firm in Spain. We show that these results hold after controlling for import tariff changes, excluding the period of the Global Financial Crisis and excluding the automotive sector. For comparison, we also construct an additional instrument for use of robots using the capabilities of industrial robots as identified from robot sales data from the IFR, in a similar way to Graetz and Michaels (2018). We find similar results using this instrument.

We further demonstrate that the sequencing of automation and offshoring matters for the impact of automation. When we focus on firms that were importing intensively from less developed countries before they starting to use robots, we find that robot use had no effect on the value of imports but decreased the share of imports sourced from developing countries, suggesting that automation does, to some degree, shift economic activity away from developing countries, but only for firms that had offshored production first. By contrast, for firms that automate first, starting to use robots has a positive impact on the probability that they import from less developed countries and the value of their imports.

Taken together, these results suggest that fears of the consequences of automation for 'reshoring' seem to have been overblown and have over-simplified what is, in fact, a complex relationship. In our sample of firms in Spain, more firms started to automate before they started to import intensively from, or open affiliates in, less developed countries. For these firms, automation generated new demand for imports and affiliates. In this paper we haven't been able to say anything about the specific products imported or the countries affected. The increase in imports could have been in less labour-intensive goods, or concentrated in middle or upper middle income countries, such as China, rather than new offshoring destinations. The increase could also reflect imports from foreign firms that have also started automating or shifted to higher tech production processes. These are all important avenues for future research.

While we do find some negative consequences for the share of imports from less developed countries, particularly after the Financial Crisis, through the channel of firms that imported intensively first

reducing their less developed country import share, we do not find any aggregate negative effects. Firms that imported intensively first did not decrease their absolute value of imports from less developed countries. For the full sample the total value of imports and the import intensity from less developed countries were also still increasing after the Financial Crisis. However, our modelling framework could imply that new entrant firms, that face an expanded task subset that is automatable, might exhibit different patterns. A further important avenue for future research is to consider whether this relationship has changed in more recent years or for new firms.

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# Appendix

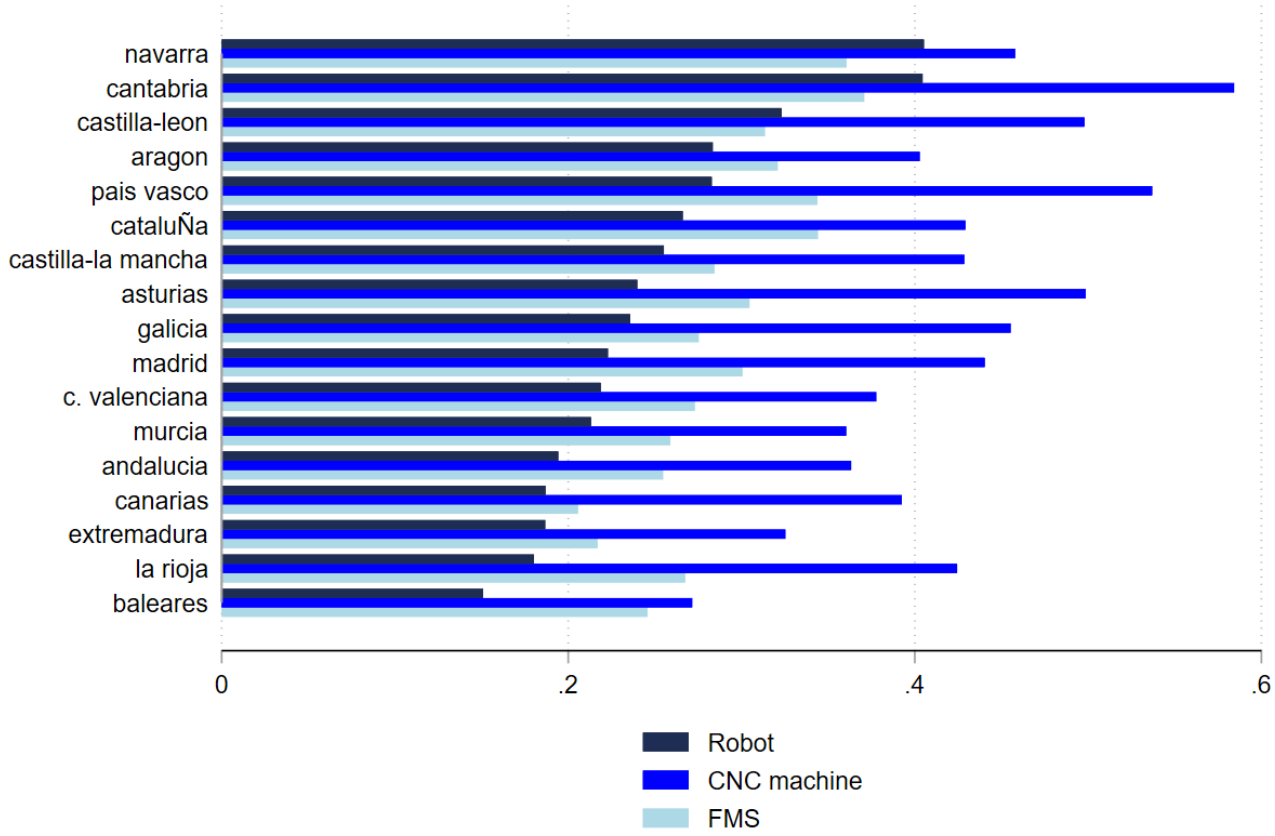
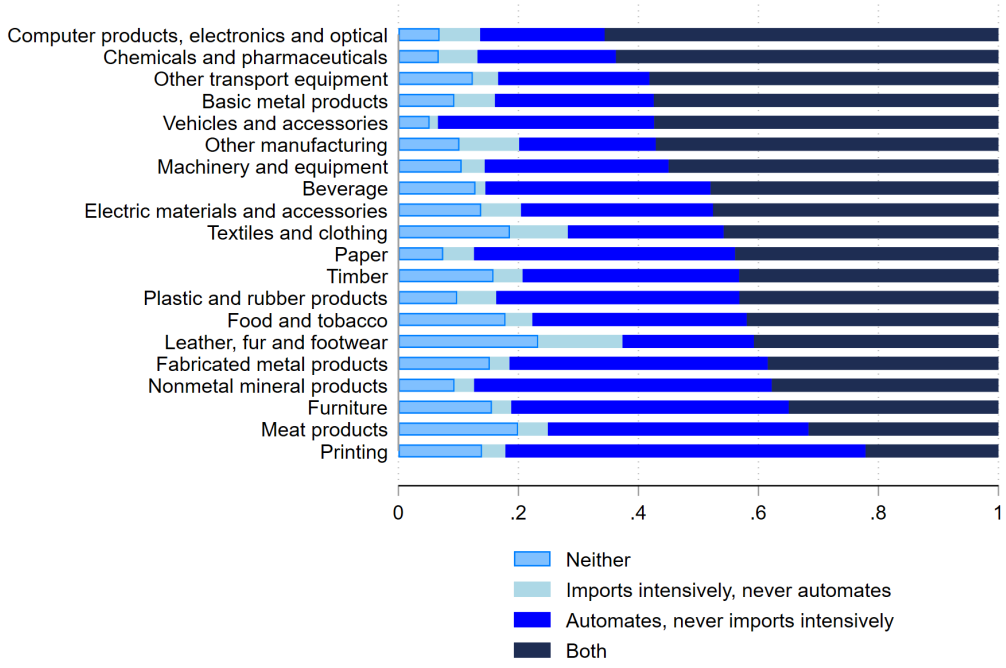
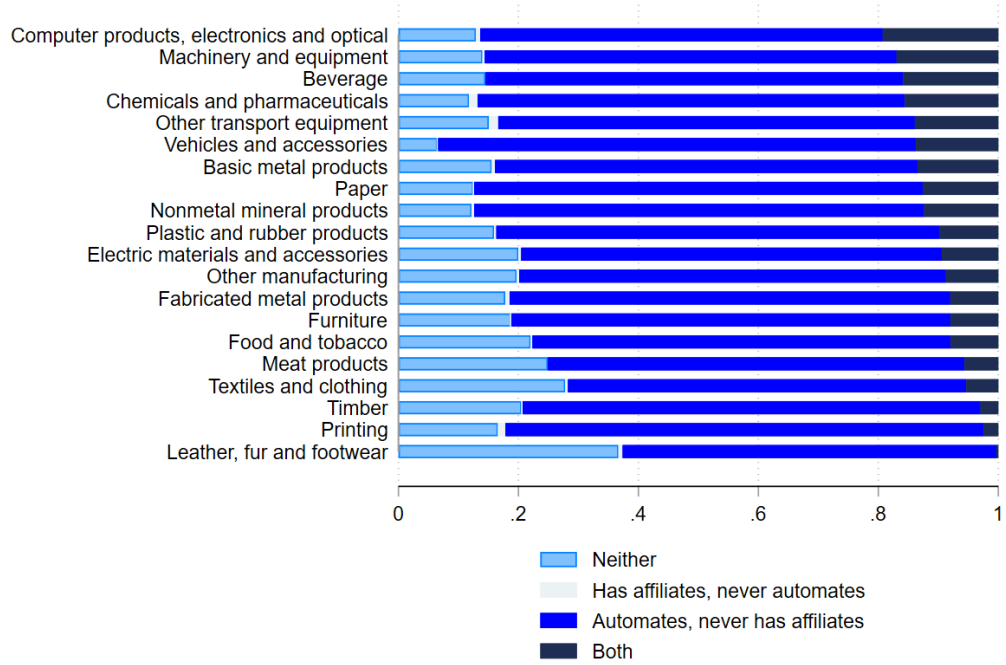



Figure 7: Technology use by region




(a) Importing intensively from less dev. countries




(b) Affiliates in less dev. countries

Figure 8: Automation, importing intensively or affiliates in less developed countries, by industry

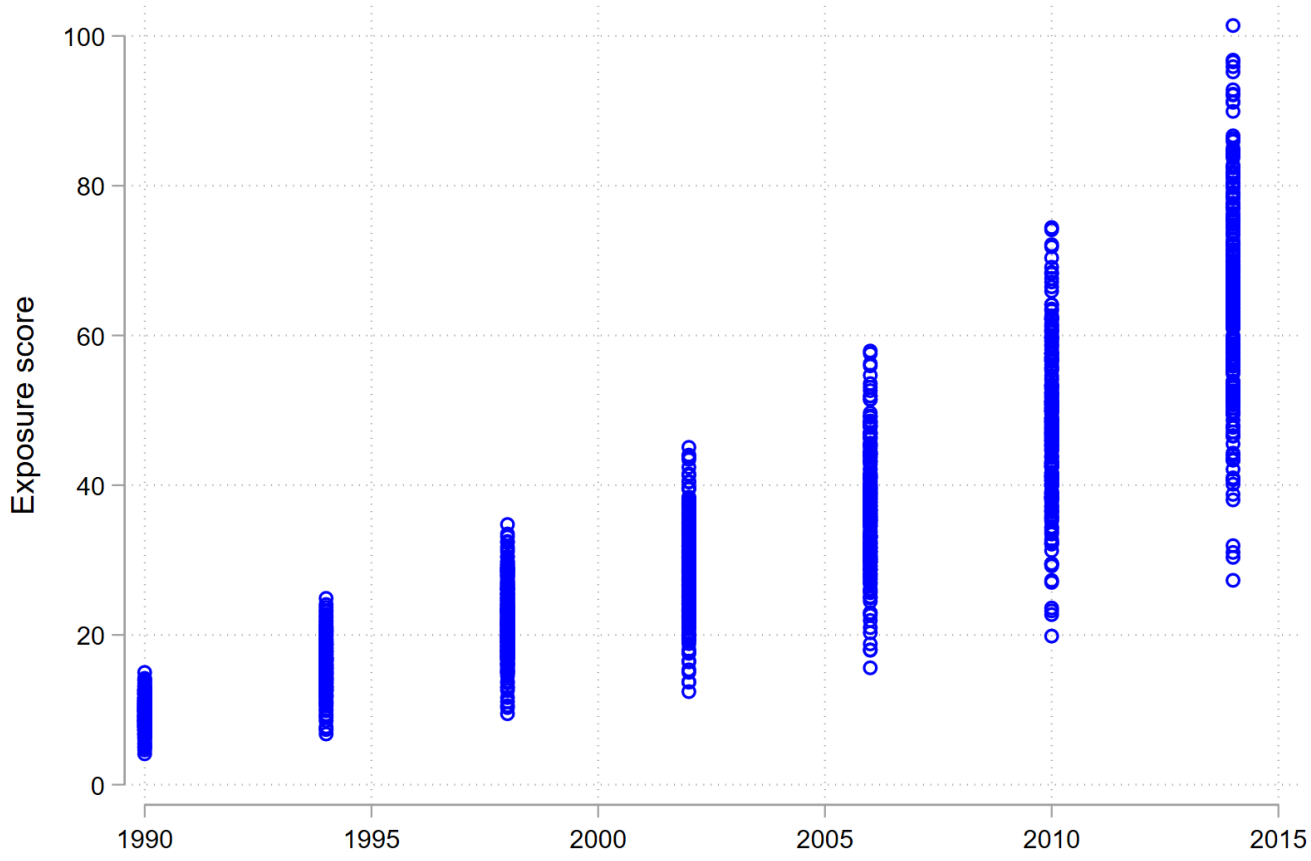



Figure 9: Patent exposure scores over time