Automation, trade and multinational activity

Micro evidence from Spain*

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August 2020

Abstract

We use a rich dataset of Spanish manufacturing firms from 1990 to 2016 to shed new light on how automation in a high-income country affects trade and multinational activity involving lower income countries. By exploiting supply side improvements in the capabilities of robots over time, as described in patents, we show that contrary 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, lower income countries. Robot use causes firms to expand production, increase productivity and increases the probability that they start importing from, or opening affiliates in, lower income countries. The sequencing of automation and offshoring has important consequences for the impact of automation, however. For firms that were offshoring to lower income countries before they starting to use robots, robot adoption had no effect on the value of imports from lower income countries, but decreased the share of imports sourced from lower income countries. By contrast, for firms that had not already offshored to lower income countries, robot adoption made them more likely to start doing so. 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

*Stapleton email: katherine.stapleton@economics.ox.ac.uk. Webb email: mww@stanford.edu. We are grateful for funding to purchase the data for for this project from Oxford's CSAE and the ESRC. We would like to thank Abi Adams, Jan Bakker, Nick Bloom, Maria Bolgova, Doug Gollin, Clement Imbert, Beata Javorcik, Peter Neary, Matthias Qian, Tony Venables and Chris Woodruff, as well as seminar participants at Oxford for insightful comments and feedback.

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 lower income countries. In a world where production is already conducted offshore, automation in a high-income country 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 lower income 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 lower income 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

[1] See, for example, Hallward-Driemeier and Nayyar (2017)

[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

access to a range of strategies to reduce their production costs, become more competitive or increase quality. The choice between these strategies depends on their relative costs and benefits. Existing research has tended to study automation at the industry level, 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 around twice as large, have around 60% higher TFP, export and import nearly four times more, are around 10% more likely to be a multinational and have an approximately 5% lower labour share than other firms in the same industry, region and year.

We find that prior to having adopted these technologies, firms that will automate in the future already import more and have more affiliates in all regions, including lower income countries, but import a lower share from lower income 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, lower income countries. When considering robots alone, firms were about as likely to have started using robots before importing intensively from lower income 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, lower income 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 lower income 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 lower income 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 lower income countries, suggesting that automation does, to some degree, shift economic activity away from lower income countries, but only for firms that had offshored production first. By contrast, for firms that started using robots before importing intensively from lower income countries, robot use has a positive impact on the probability that they start to import from lower income countries and the value of their imports. The effect for the latter group dominates, such that the aggregate impact of robots on imports from lower income countries is positive.

In terms of the consequences for firm operations within Spain, we find that robot use also caused firms to substantially expand production and increase both labour productivity and TFP, with some evidence of a decrease in the 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 employed and a weak increase in the number of production workers.

We demonstrate that these key results hold after controlling for global supply side shocks that have made offshoring cheaper and easier, 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 incorporating two new aspects into the canonical task-based automation model of Acemoglu and Restrepo (2018). First, we additionally incorporate Melitz (2003) style firm heterogeneity into the the task based framework and second, we allow for the additional option to offshore tasks as well as automate them, following from a variant in Acemoglu and Autor (2011) that incorporates offshoring in addition to automation. 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.

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 lower income 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, lower income 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 lower income 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 lower income countries. Secondly, there are a subset of firms that switch into importing from, or opening affiliates in, lower income 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 of automation. 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 lower income 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 lower income countries. This implies that a large enough market stealing effect could also result in a shift in the composition of imports away from lower income 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 explore the characteristics of firms that automate and the sequencing of automation, importing and multinational activity. 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

Existing frameworks have tended to model the impact of automation at the economy-wide or industry level and have focused on the impacts on domestic labour markets, abstracting away from the role of the firm or the interaction between automation and international trade. In this model we aim to incorporate these two new aspects into the task based framework for studying automation of Acemoglu and Restrepo (2018). First, we include Melitz (2003) style firm heterogeneity. Second, we include the additional option for firms to offshore, as well as automate, tasks. 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 ω 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. 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 ω involves performing tasks $x \in [0, 1]$. The output of firm ω 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 ω and σ 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 $m(x)$.[3] Following Acemoglu and Restrepo (2018), we assume that labour in the home country, labour in the offshore country and machines are perfectly substitutable factors of production. Assume the tasks are ordered by the productivity of home labour in completing them, $\gamma_{LH}(x)$.

2.2 Production with only offshoring

We assume 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 a high-income 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 τ 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:

$$q(\omega, x) = \begin{cases} \mathbb{1}[H=1]\gamma_{LH}(x)l_H(\omega,x) + \mathbb{1}[O=1]\frac{\gamma_{LO}(x)l_O(\omega,x)}{\tau} & \text{if } x \in [0, I^O] \\ \\ \gamma_{LH}(x)l_H(\omega,x) & \text{if } x \in [I^O, 1] \end{cases} \tag{2}$$

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. Analogously to in Acemoglu and Restrepo (2018), 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.

Combining these equations, defining γ^{τ}_{LO} as the productivity of offshore labour adjusted to take into account iceberg costs and denoting $\Gamma_F^{(a,b)} = \left(\int_a^b \gamma_F(x)^{\sigma-1}dx\right)$, where F is either L_O, L_H or M, and $F^{(a,b)}(\omega) = \int_a^b f(\omega,x)dx$, where f is either l_H, l_O or m, we can write the firm's output if

[3] Machines could be used in either the home or offshore country. In our empirical analysis we can only observe use of robots in the firm in Spain, so focus on the use of machines at home. In general, the use of industrial robots per capita has been shown to be greater in high income countries, where robot manufacturing is generally concentrated and labour costs higher (IFR, 2019).

they choose to offshore $q^O(w)$ or if they do not offshore $q(w)$ as:

$$q^O(\omega) = \varphi(\omega)\left(\Gamma_{LO}^{(0,I^O)} L_O^{(0,I^O)}(\omega)^{\frac{\sigma-1}{\sigma}} + \Gamma_{LH}^{(I^O,1)} L_H^{(I^O,1)}(\omega)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} \tag{3}$$

and

$$q(\omega) = \varphi(\omega)\left[\Gamma_{LH}^{(0,1)} L_H^{(0,1)}(\omega)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \tag{4}$$

2.3 Preferences and profit maximisation

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 ω , 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 measure of existing varieties and E is the aggregate level of spending in the country.

The profit maximising price is a constant markup over marginal costs. We consider 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:

$$MC^O(\omega) = \frac{1}{\varphi(\omega)}\left(\Gamma_{LO}^{(0,I^O)} w_O^{1-\sigma} + \Gamma_{LH}^{(I^O,1)} w_H^{1-\sigma}\right)^{\frac{1}{1-\sigma}} \tag{5}$$

$$MC(\omega) = \frac{1}{\varphi(\omega)}\left(\Gamma_H^{(0,1)} w_H^{1-\sigma}\right)^{\frac{1}{1-\sigma}} \tag{6}$$

Taking the second part of the right hand side of 6, $\left(\Gamma_H^{(0,1)} w_H^{1-\sigma}\right)^{\frac{1}{1-\sigma}}$ as the numeraire and equating this to 1, we can then write the marginal cost functions as:

$$MC^O(\omega) = \frac{\alpha}{\varphi(\omega)} \qquad \text{and} \qquad MC(\omega) = \frac{1}{\varphi(\omega)} \tag{7}$$

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

2.3.1 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:

$$\pi^O(\varphi(\omega)) = (1-\rho)EP^{\frac{\rho}{1-\rho}}\left[\frac{1}{\rho}MC^O\right]^{\frac{-\rho}{1-\rho}} - F_O - F_e \tag{8}$$

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

And so they will offshore if $\pi^O(\varphi(\omega)) > \pi(\varphi(\omega))$. There is a productivity cutoff φ^* 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:

$$\pi^O(\varphi(\omega)) - \pi(\varphi(\omega)) > 0 \Leftrightarrow \Omega(\varphi(\omega))(\alpha^{\frac{-\rho}{1-\rho}} - 1) > F_O \tag{10}$$

and φ^* is the productivity corresponding to the firm where:

$$\Omega(\varphi^*(\alpha^{\frac{-\rho}{1-\rho}} - 1) = F_O \tag{11}$$

2.4 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:

$$q(\omega,x)=\begin{cases}\mathbb{1}[H=1]\gamma_{LH}(x)l_H(\omega,x)+\mathbb{1}[O=1]\frac{\gamma_{LO}(x)l_O(\omega,x)}{\tau}+\mathbb{1}[M=1]\gamma_M(x)m(\omega,x) & \text{if}\, x\in[0,I^M]\\ \\ \mathbb{1}[H=1]\gamma_{LH}(x)l_H(\omega,x)+\mathbb{1}[O=1]\frac{\gamma_{LO}(x)l_O(\omega,x)}{\tau} & \text{if}\, x\in[I^M,I^O]\\ \\ \gamma_{LH}(x)l_H(\omega,x) & \text{if}\, x\in[I^O,1]\end{cases} \tag{12}$$

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:

$$q^{OM}(\omega)=\varphi(\omega)\left(\Gamma_M^{(0,I^M)}M^{(0,I^M)}(\omega)^{\frac{\sigma-1}{\sigma}}+\Gamma_{LO}^{(I^M,I^O)}L_O^{(I^M,I^O)}(\omega)^{\frac{\sigma-1}{\sigma}}+\Gamma_{LH}^{(I^O,1)}L_H^{(I^O,1)}(\omega)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} \tag{13}$$

$$q^{M}(\omega)=\varphi(\omega)\left(\Gamma_M^{(0,I^M)}M^{(0,I^M)}(\omega)^{\frac{\sigma-1}{\sigma}}+\Gamma_{LH}^{(I^M,1)}L_H^{(I^M,1)}(\omega)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} \tag{14}$$

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.

2.4.1 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:

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

$$MC^{M}(\omega) = \frac{1}{\varphi(\omega)}\left(\Gamma_M^{(0,I^M)} r^{1-\sigma} + \Gamma_{LH}^{(I^M,1)} w_H^{1-\sigma}\right)^{\frac{1}{1-\sigma}} \tag{16}$$

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

$$MC^{OM}(\omega) = \frac{\beta}{\varphi(\omega)} \qquad \text{and} \qquad MC^{M}(\omega) = \frac{\delta}{\varphi(\omega)} \tag{17}$$

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 α relative to δ, 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:

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

$$\pi^{OM}(\varphi(\omega)) = (1-\rho)EP^{\frac{\rho}{1-\rho}}\left[\frac{1}{\rho}MC^{OM}\right]^{\frac{-\rho}{1-\rho}} - F_M - F_O - F_e \tag{19}$$

There are now two additional productivity cutoffs associated with automating φ^{M*} and both automating and offshoring φ^{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.

2.5 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.

2.5.1 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 either home labour if they hadn't offshored or offshore labour if they had, towards machines, and also a positive productivity effect.

2.5.2 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.

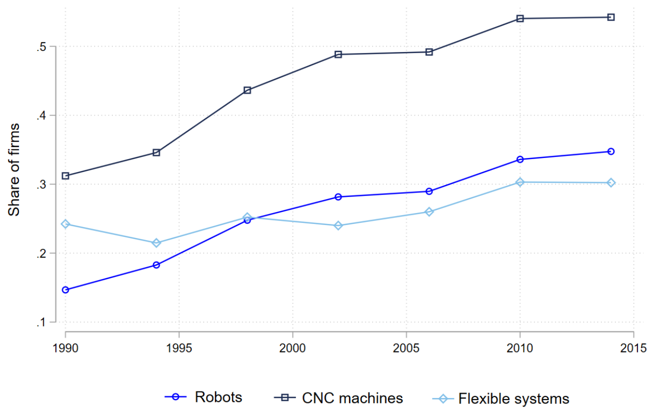
3. Data

3.1 Spanish firms data

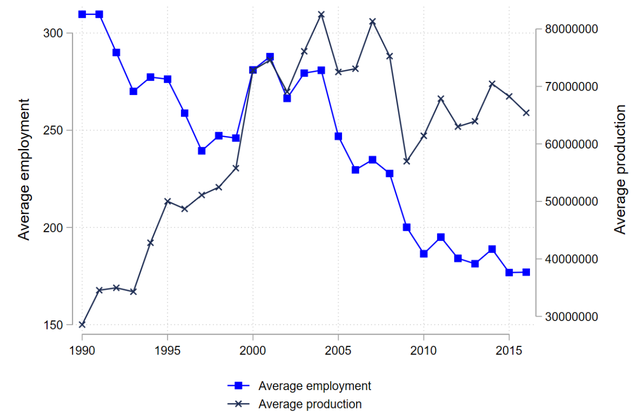
The primary data source used in this paper is the 'Encuesta Sobre Estrategias Empresariales' (ESEE), an annual survey of Spanish manufacturing firms carried out by the SEPI Foundation in conjunction with the Spanish Ministry of Industry between 1990 and 2016.[4] This dataset is relatively unique in providing 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

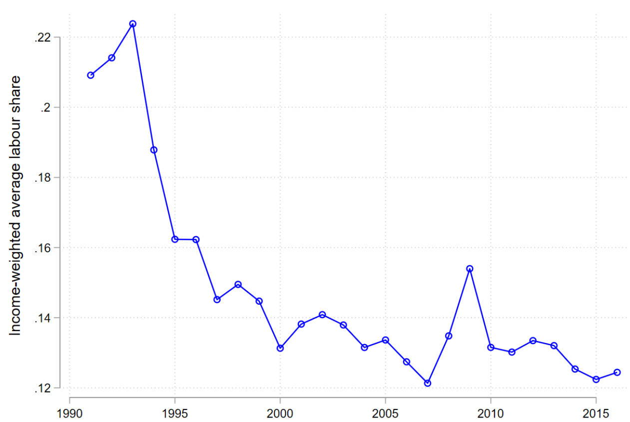
[4] https://www.fundacionsepi.es/investigacion/esee/en/spresentacion.asp



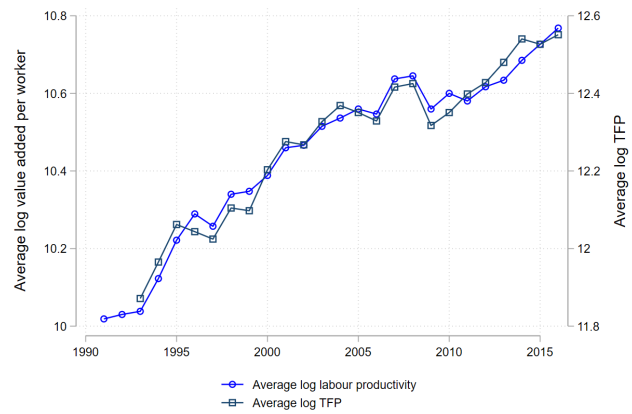
(a) Technology adoption



(b) Employment and production



(c) Labour share



(d) Productivity

Figure 1: Key domestic outcomes over time

Notes: Panel (a) displays the share of firms in the sample that report using the three technologies. Panel (b) displays the mean value of production of goods or services and the mean employment across all firms. Panel (c) displays the income-weighted average labour share across all firms. Panel (d) displays the mean logged value added per worker and logged TFP across all firms.

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 used in the manufacturing sector typically perform industrial applications including welding, material handling, assembly, palletizing, and painting. The 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' (IFR, 2019). The ESEE does not specify the type of robots used. However, given the survey covers manufacturing firms and up to 2016, when collaborative robots were less widely commercially available, we assume these are likely to be primarily industrial robots.

2. **FMS:** An FMS combines CNC machines, industrial robots, and other types of automation into 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.[5] There are 20 industries in the ESEE data using the Spanish NACECLIO classification system, which is based on the NACE.[6] 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 Leather, Fur and Footwear, Printing and Textiles and Clothing. In Table 16 in Appendix B we also display the correlation between use of

[5] In Appendix A, Figure 8 also displays technology adoption by region.

[6] 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.

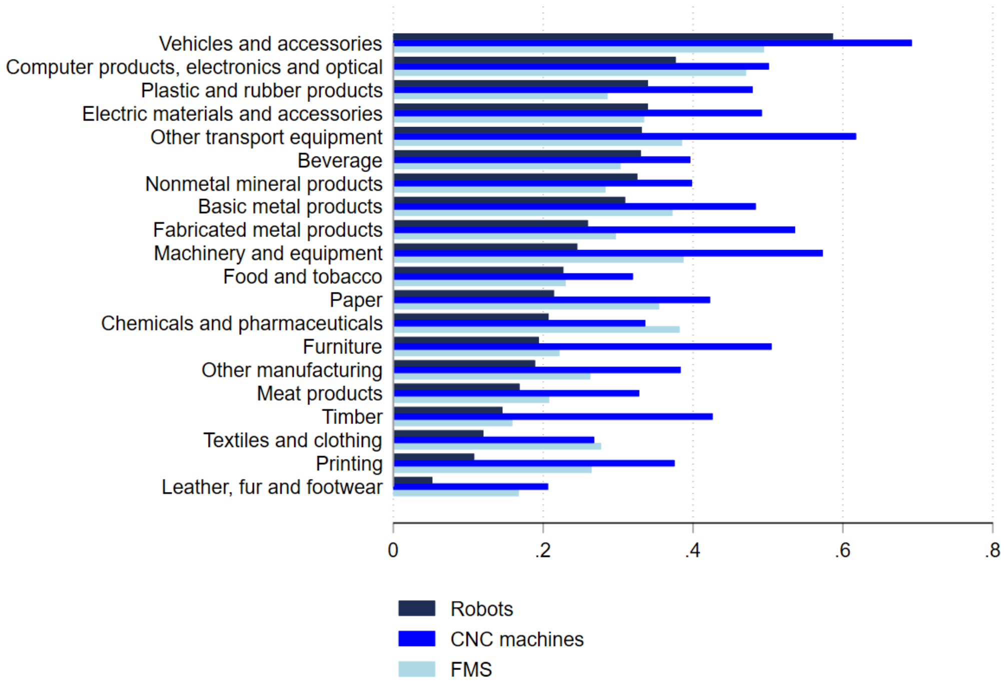


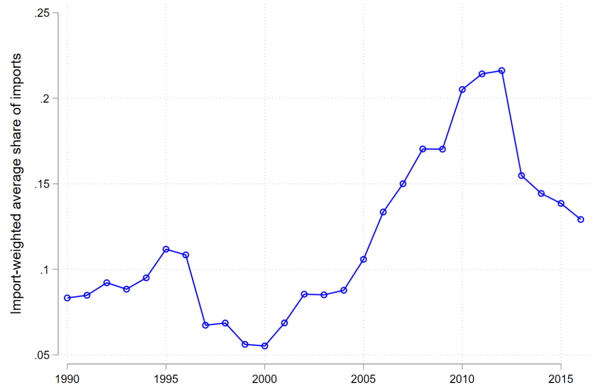
Figure 2: Share of firms using each technology, by industry

Notes: This figure displays the share of firms using each of the three technologies across all time periods, by industry.

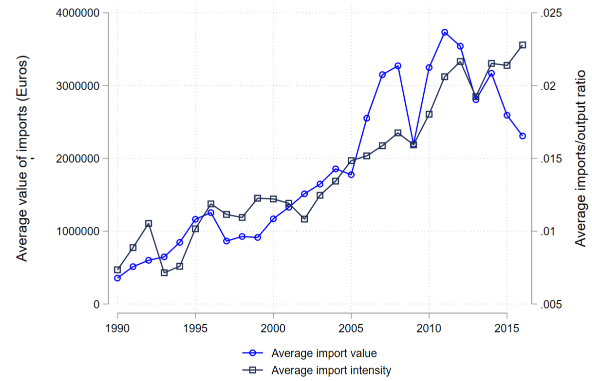
these three technologies, which is highest for robots and CNC Machines at 0.34 and lowest for FMS and CNC Machines at 0.18.

Additionally the ESEE data provides annual investment by type, with one of the categories the 'purchase of technical facilities, machinery and tools'. We use this, along with the firm level depreciation rate, to construct the firm level stock of industrial machinery and equipment, discussed later in the paper.

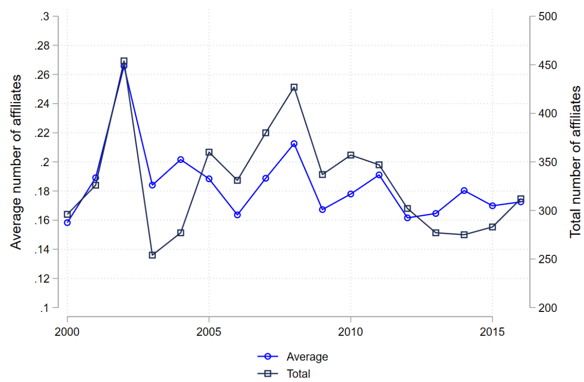
Trade and multinational activity variables: The key trade-related variables we use are the value of imports and breakdown of imports by region. Firms provide exports and imports broken down into region groups: the EU, OECD countries excluding the EU, Latin America and the Rest of World. We combine the sum of Latin-America and Rest of World to form a broad measure of trade with 'lower income countries'. We list the countries in these groups in Appendix **??**. In terms of total import value cumulatively between 1990 and 2016, Spain's largest import partners in this lower income group were China, with 5.5% of imports, Algeria, with 1.8%, Nigeria with 1.6%, Russia with 1.5%, Saudi Arabia with 1.2%, Brazil with 1.1%, Morocco with 1%, Libya



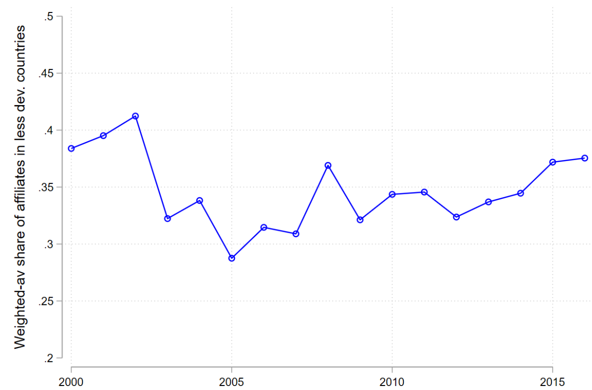
(a) Import share from less dev. countries



(b) Value of imports & import intensity



(c) Affiliates in less dev. countries



(d) Share of affiliates in less dev. countries

Figure 3: Key international outcomes over time

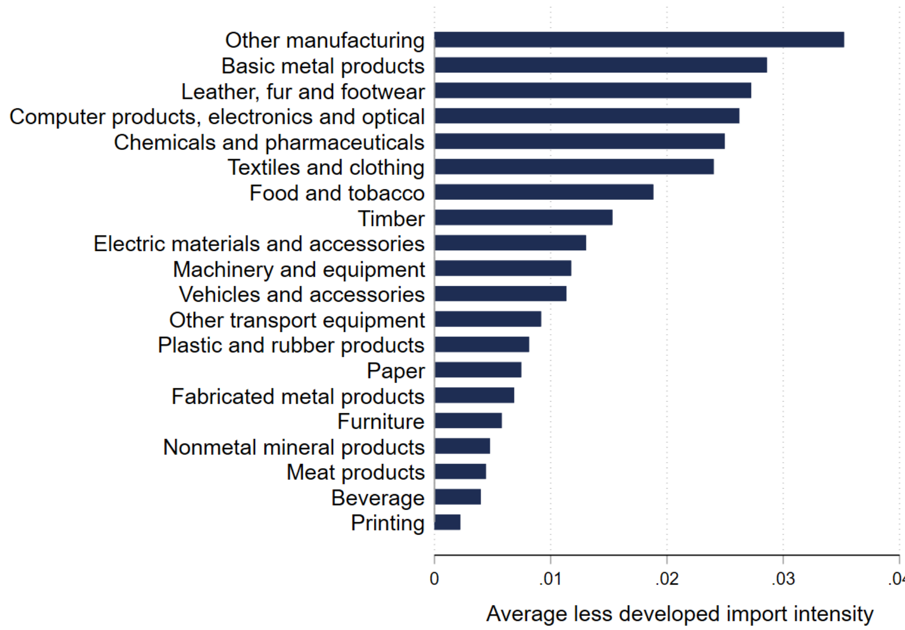
Notes: Panel (a) displays the import-weighted average share of firm imports that originate from lower income countries, averaged across all firms. Panel (b) displays the mean value of imports from lower income countries and the mean import intensity from lower income countries, defined as the value of imports from lower income countries scaled by firm output. Panel (c) displays the mean number of affiliates in lower income countries and the total number, across all firms. Panel (d) displays the weighted-average share of affiliates in lower income countries, across all firms.

with 0.8%, India with 0.8% and Indonesia with 0.6%, based on UNCOMTRADE import data. Membership of the EU and OECD changed slightly over time and we document these changes in Table 23 in Appendix **??**. The group of countries that switch into the lower income category during our sample period account for a relatively small amount of Spain's imports, at around 6%. We include industry group-year fixed effects in our empirical specifications, which should absorb these changes to categorisation that we expect would affect all firms equally, or at least all firms in the same industry groups equally.

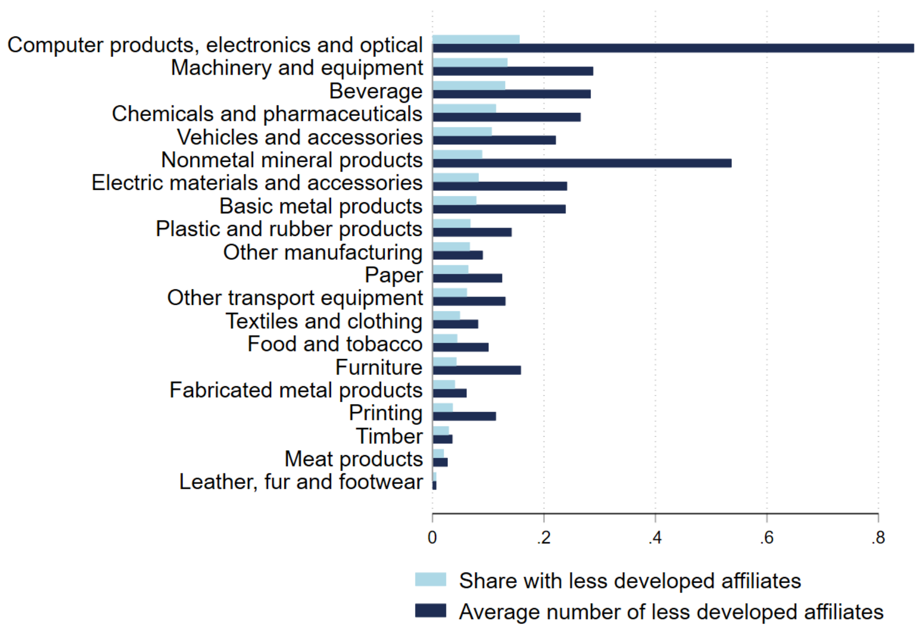
Our primary outcome variables are a dummy variable for whether a firm imports from this group of lower income countries, the share of imports from this group and the intensity of imports from this group, measured as imports relative to output. Additionally, firms provide their number of affiliates by these same region groups, the country of the 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 lower income countries and the share of affiliates in lower income 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



(a) Import intensity



(b) Affiliates

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

Notes: Panel (a) displays the mean import intensity from lower income countries across all years, by industry, where import intensity is defined as the value of imports from lower income countries scaled by output. Panel (b) displays the share of firms with at least one affiliate in a lower income country and the mean number of lower income affiliates, across all years, by industry.

and 2016 the mean value of imports from lower income countries and the intensity of imports from lower income countries, have increased approximately six-fold.[7] The import-weighted share of imports from lower income countries approximately tripled between 1990 and 2010 but has then fallen. There is a less clear pattern for affiliates in lower income countries. Figure 4(a) displays the import intensity from lower income 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 lower income countries and the average number of affiliates in lower income countries, by industry. The three industries with the highest share of firms having affiliates in lower income countries are Computer products, electronics and optical, Machinery and equipment and Beverage.

Measuring TFP: Our main measure of TFP is constructed 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 or missing in just over 14% of observations), while there is better data coverage for intermediate inputs (zero or missing for only 0.6% of observations). The ESEE data 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. We use the sales price change to deflate the value of total income, which is the sum of firm production of goods and services and other income, the average of the change in energy and raw materials prices to deflate the value of intermediate purchases of goods inputs and the services price change to deflate the value of intermediate purchases of services inputs.

The ESEE data doesn't provide firm level price changes for capital, so we use the gross fixed capital formation price index for the manufacturing sector for Spain from the Capital Input Files from EUKLEMS.[8] We construct real value added as the real value of total income minus the real value of intermediate inputs of goods and services and we use real value added as the dependent variable. We measure labour in terms of the average total employment at the firm, provided in the ESEE data. This is calculated as the sum of the following items: Full-time regular personnel,

[7] The same holds for the total value of imports from lower income countries across all firms included in the data.
[8] http://www.euklems.net/

1/2 of the part-time regular personnel and the average number of temporary workers. Given our data only covers manufacturing industries and the sample size too small to estimate TFP for individual sub-manufacturing sectors, we instead split the manufacturing industries into two broad groups and estimate TFP for each group.[9] As a robustness check, in Appendix B we also repeat all results using TFP constructed by the Olley-Pakes method instead, showing that there is only a slight difference in magnitudes of coefficients between these two estimates.

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 worker and the labour share of income.[10] 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

[9]These groups 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 in one group and 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 in the other group

[10]Following consensus in the literature we define the labour share as total labour costs, divided by total income, both variables that are directly reported in the ESEE data.

TABLE 1. SUMMARY STATISTICS

	Mean	S.d.	Min	Max
Variables in levels				
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*machinery stock	6.8e+14	1.1e+17	0	2.32e+19
Patent exposure measure	33.8	20.1	5.00	118.4
IFR exposure measure	0.28	0.26	0	0.89
IFR robot stock (millions)	0.92	0.34	0.56	1.83
Share of imports from less dev countries	0.44	0.47	0	1
Imports from less dev countries (euro millions)	1.85	22.5	0	1626.5
Import intensity from less dev countries	0.014	0.055	0	1.54
Affiliates in less dev countries	0.18	1.55	0	100
Share of affiliates in less dev countries	0.043	0.18	0	1
Employment	239.6	767.8	1	24634
Output (euro millions)	59.7	292.1	5.4	8923.4
Labour share	0.29	0.35	0.0049	59.0
Transformed variables				
Robot user*log machinery stock	4.35	7.02	0	44.6
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
Log employment	4.20	1.50	0	10.1
Log output	15.8	2.03	8.59	22.9
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.

Housing and Population is the most comprehensive data source on employment in these three dimensions.

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.[11] 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

[11] https://bigquery.cloud.google.com/table/patents-public-data:patents.publications201710

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 ISO definition provided above. 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 Offshoring instrument control

As a robustness check, we develop a control variable for exogenous supply-side factors that may have affected a Spanish firm's propensity to offshore production, that are unrelated to automation. We construct a variable similar to the 'World Export Supply' instrument used in Hummels et al. (2014) that aims to soak up supply shocks occurring within Spain's import partner destinations, for example, the rise of China as a manufacturing hub. To do so, we make use of the import share variables in the ESEE data that break down imports by the four regional groups discussed above. We use these shares in the firm's first reporting period to weight industry level exports from all countries in these region groups to four EU countries with the closest GDP per capita to Spain.[12]

We take this export data by ISIC Rev 3 industry from UNCOMTRADE, accessed via the WITS platform from the World Bank.[13] We use an ISIC Rev 3-NACE Rev 1 Crosswalk provided by Eurostat to map these to NACE Rev 1 industries.[14] The Spanish NACECLIO industry classification is based upon NACE Rev 1 so we can then easily map these to the ESEE industries. In order to ensure the measures reflect supply shocks in the industries that Spanish firms are likely to source their intermediate imports from, we further apportion the industry level exports to other

[12] These countries are Italy, Portugal, Slovenia and the Czech Republic.
[13] wits.worldbank.org
[14] https://ec.europa.eu/eurostat/ramon/relations/index.cfm?TargetUrl=LST_REL

industries according to the baseline purchase share specified in Spain's I-O table for imports obtained from the Instituto Nacional D'Estistica (INE). [15] Then for firm i in industry j at time t, the instrument for offshoring O_{ijt} is defined as:

$$O_{ijt} = \sum_{c} s_{ijc,base} \times \text{IO share}_{jk,base} \times EX_{ckt} \tag{20}$$

where $s_{ijc,base}$ is firm i in industry j's share of imports from region group c in their first reporting period, $\text{IO share}_{jk,base}$ is the IO share of sourcing industry k in purchasing industry j's total imports in 1995 and EX_{ckt} is the value of total exports from region group c in industry k to the four countries similar to Spain.

3.6 Import tariff controls

As a robustness check we also develop a control variable for changes to Spain's import tariffs that may have affected the cost of importing from lower income countries or the opening of affiliates in lower income 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. We take the simple average tariff in each ISIC Rev 3 product category in each year and use the ISIC Rev 3-NACE Rev 1 Crosswalk discussed above 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. For the imported input tariffs we further weight these tariffs using the IO import table weights obtained from the INE, as described above.

TABLE 2. PREVALENCE & 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.

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 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.

[15] 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 lower income)	1.57	1.70	2.53	1.03	1.15	1.76	1.50	1.85	2.03
Import share from lower income	-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 lower income 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.

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:

$$X_i = \alpha + \beta \text{Technology}_i + \gamma \text{Industry}_i + \theta \text{Region}_i + \epsilon_i \tag{21}$$

where X_i is the outcome of interest, Technology$_i$ is a dummy variable for firm use of one of the three technologies: robots, CNC or FMS, Industry$_i$ is the firm's 2 digit industry and Region$_1$ is the Spanish autonomous community where the firm is headquartered.[16] 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 reports these premia, where for all of the technologies in all of the

[16]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	1.15	0.85	0.92	0.86	0.76	0.69	1.06	0.88	0.96
Log value added per worker	0.26	0.22	0.17	0.27	0.20	0.22	0.27	0.36	0.25
Log TFP	0.65	0.55	0.59	0.53	0.53	0.56	0.65	0.62	0.61
Log output	1.49	1.17	1.20	1.24	1.13	1.03	1.40	1.19	1.29
Labour share	-0.057	-0.062	-0.073	-0.079	-0.068	-0.073	-0.063	-0.048	-0.064
				Panel (b): International trade					
Exporter	0.24	0.20	0.17	0.19	0.17	0.16	0.23	0.20	0.17
Importer	0.24	0.20	0.21	0.21	0.18	0.12	0.25	0.21	0.16
IHS(exports)	4.16	3.59	3.47	3.34	2.92	3.16	4.05	3.89	3.56
IHS(imports)	4.23	3.57	3.72	3.44	3.03	2.31	4.15	3.59	3.09
IHS(imports from lower income)	0.88	0.94	1.64	1.06	1.36	1.09	1.10	0.93	1.01
Import share from lower income	-0.23	-0.19	-0.20	-0.19	-0.16	-0.092	-0.24	-0.20	-0.16
				Panel (c): Multinational activity					
Multinational		0.083	0.092		0.066	0.080		0.14	0.12
IHS(total number of affiliates)		0.15	0.11		0.13	0.100		0.23	0.17

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 at any point in the future. 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.

time periods these premia are statistically significant to the 1% level 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 lower income countries but the share of their imports from lower income countries is around 17% lower. 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 lower income countries. The premia for the share of affiliates in lower income 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 at any point 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:

$$X_{it} = \alpha + \beta \text{FutureTechnology}_{it} + \gamma \text{Industry}_{it} + \theta \text{Region}_{it} + \epsilon_{it} \tag{22}$$

where X_{it} is the outcome of interest for firm i in period t, $\text{FutureTechnology}_{it}$ is a dummy variable for firm use at any point in the future recorded in the data 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. We limit the sample to only firms that remain in the sample for at least 5 years so that we compare firms where we have the information on whether they adopted these technologies in the future.

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, except for the number of affiliates in lower income countries. 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.

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 lower income countries, although their import share from lower income countries is lower. But it is not yet clear which is causing the other. We hence further consider the timing of when firms

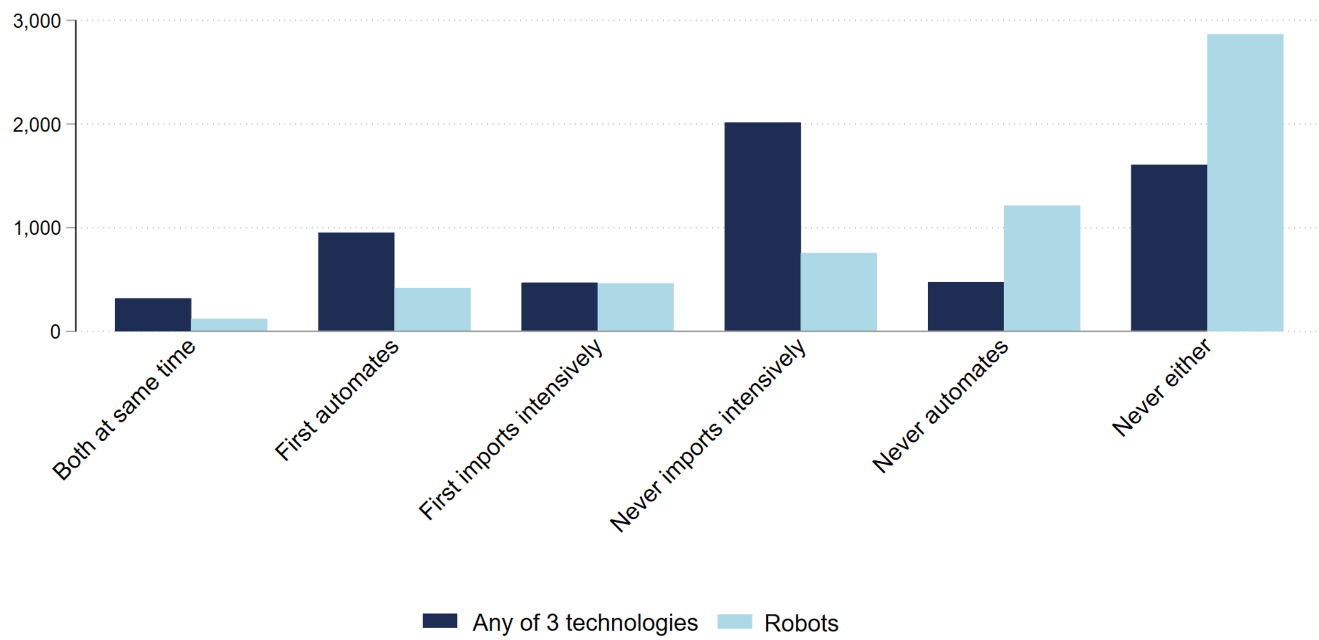


Figure 5: Sequencing of automation and importing intensively from lower income countries

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

automate and when they start importing intensively or opening up affiliates in lower income countries. We define importing intensively from lower income countries as being in the top 20th percentile in terms of the ratio of imports from lower income 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, lower income countries, then later report automating, followed by a decline in import intensity or affiliates in lower income countries. Figure 5 shows that, in fact, far more firms started automating, using any one of these three technologies, before they started importing intensively from lower income countries. Only 36% of firms ever import intensively from lower income 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. In terms of only those that automate only 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 lower income countries. For firms that do both, they are almost equally likely to be importing intensively before they automate as vice versa.[17]

Having an affiliate in a lower income country is far less common than importing intensively from lower income countries. Only 6% of our sample ever report having affiliates in lower income 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 lower income countries but never automating. Of those that have affiliates in lower income 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

[17]In Figure 5 in Appendix A we provide this graph defining importing intensively instead as being in the top 20th percentile within the same industry in terms of the ratio of imports from lower income countries to output, demonstrating that the same conclusions hold.

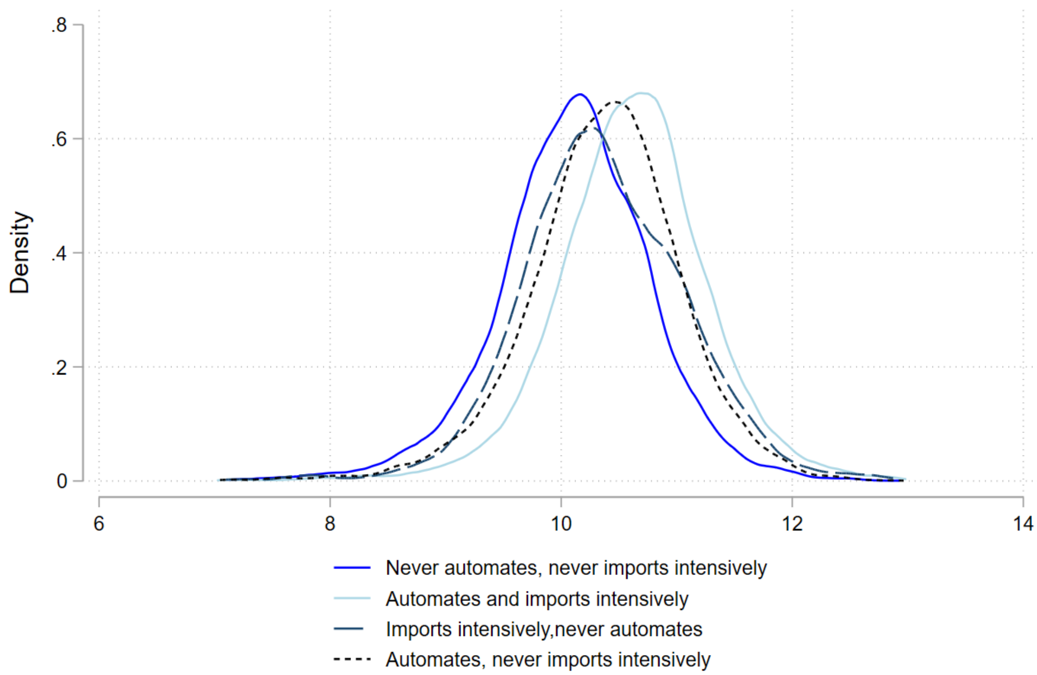


Figure 6: Labour productivity distribution by automation and importing from lower income countries

Notes: This figure displays the distribution of the log of value added per worker for the four groups of firms in terms of whether they automate using any of the three technologies at any point in the data and whether they import intensively from lower income countries, defined as being in the top 20% of the sample, at any point in the data.

least productive firms doing neither. We show in Figure 6 that this is the case in our data. We define automating and importing intensively as above. 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. In Figure 10 in Appendix A we provide the analogous figure for affiliates in lower income countries. Again the distribution of firms that both automate and have affiliates in lower income 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 11 in Appendix A 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' 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 attempting to evaluate the causal impact of automation on our key firm outcomes, focusing from this point onwards on robot use only. The baseline specification we aim to estimate is:

$$\mathrm{X}_{it} = \alpha + \beta \mathrm{Robots}_{it} + \theta \text{industry-year}_{it} + \phi \text{region-year}_{it} + \gamma_i + \epsilon_{it} \tag{23}$$

where X_{it} is the outcome of interest for firm i in year t, Robots_{it} is a dummy variable for firm use of robots at time t and γ_i, industry-year$_{it}$ and region-year$_{it}$ are firm, industry-year and region-year fixed effects.[18] By including firm fixed effects our specification estimates the impact of changes in robot use within firms over time. The inclusion of industry-year fixed effects aims to soak 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.

5.1 Identification challenges

There are two major identification challenges when estimating the model in equation 23. First, this equation could suffer from reverse causality. In Section 4 we demonstrated that firms that select into automation in the future have distinct characteristics in terms of their international orientation, size and productivity, relative to firms that do not. It is possible that firm-level time-varying changes to importing or multinational activity could affect time-varying changes to robot adoption. There is recent evidence from Bernard et al. (2019), for example, that firms that offshore subsequently reorganise production, shifting activities at their headquarter firms towards more innovative and technology-focused production. If this also applied to the adoption of technologies, such as robots, and varied between firms within the same industry or region in a given year, then the demeaned robot use dummy variables could be correlated with the demeaned error term, resulting in biased estimates. Second, there could be unobserved firm-level time varying shocks that affect both robot adoption and the outcome variables. For example it is plausible that there could be firm-specific shocks to labour demand or trade that also affect the decision to automate.

In order to isolate the causal impact of robot use on firm performance and offshoring, we hence construct two separate instruments that should influence robot adoption over time but should not directly affect firm outcomes, such as importing or multinational activity. The first follows Webb (2019) and maps globally filed robotics patents to occupations conducting similar tasks. We then use the ex-ante 'exposure' of industry-region pairs to advances in robotics over

[18] The robot use dummy variables are provided every four years. In the case where the firm reports using or not using robots at both end of the four year period, we assume it continues to do the same in the years in between. In the case where the firm switches between the start and end of the period, we assume the switch occurs between the second and third intermediate years.

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.

5.2 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, were 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 hand construct a crosswalk between the O*NET SOC codes and ISCO 68 codes.[19] 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:

$$\text{robot}_{irjt} = \text{exposure}^{robotpatent}_{rjt} \tag{24}$$

where

$$\text{exposure}^{robotpatent}_{rjt} = \sum_{o=1}^{n} \text{automatable}^{patent}_{ot} \times \text{employment}_{orj1981} \tag{25}$$

where $\text{automatable}^{patent}_{ot}$ is the patent measure of automatability for occupation code o in year t and $\text{employment}_{orj1981}$ is the employment share of occupation o in region r and industry j in 1981.

We estimate 23 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

[19] We construct our own crosswalk because we could not find an established crosswalk from O*NET to ISCO 68 without combining multiple different crosswalks to go from O*NET to US SOC to ISCO88 then to ISCO68. We are happy to share this crosswalk and make it available on request.

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.[20]

5.2.1 Insights from exposure measures

Most and least exposed occupations: Table 17 in Appendix B displays the ISCO 68 occupations with the highest and lowest exposure scores scores. A more detailed discussion on the original O*NET SOC exposure scores can be found in Webb (2019). The most exposed occupations include various kinds of materials movers in factories and warehouses, and tenders of factory equipment. The most exposed category is 'Material-Handling and Related Equipment Operators, Dockers and Freight Handlers'. The least-exposed occupations include clergy, government administrators, accountants, jurists and authors. These do not primarily involve the kinds of repetitive manual tasks that robots automate.

Most and least exposed industries and regions: Figure 7 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.

5.3 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 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

[20]These groups are: 1. Heavy Manufacturing with the following industries included: industries Chemicals and pharmaceuticals, Plastic and rubber products, Nonmetal mineral products, Basic metal products, Fabricated metal products and Machinery and equipment and Timber. 2. Light manufacturing with the following industries included: Meat products, Food and Tobacco, Beverage, Textiles and Clothing, Leather, fur and footwear, Paper and Printing. 3. Complex manufacturing with te following industries included: Computer products, electronics and optical, Electric materials and accessories, Vehicles and accessories, Other transport equipment, furniture and Other manufacturing.

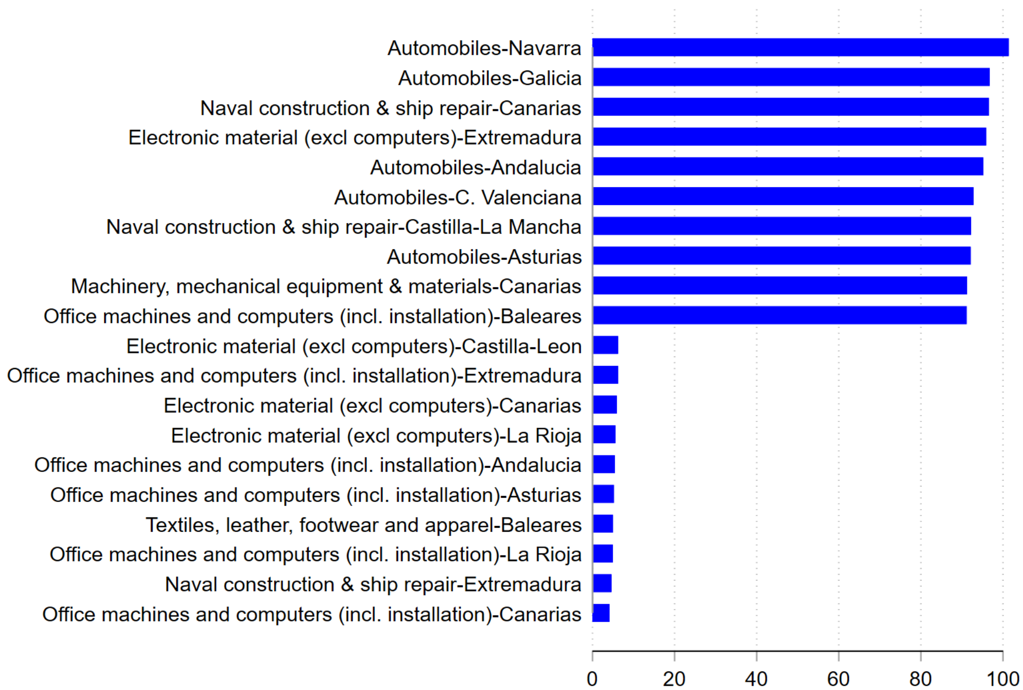


Figure 7: Top 10 industry-region pairs with highest and lowest median exposure

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

'arc welding'. In a similar vain to Graetz and Michaels (2018) we hand match robot applications to ISCO 68 occupation codes.[21] 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.

5.4 Threats to identification

The identifying assumption for our patent-derived instrument is that the demeaned transformation of the 1981 occupational employment shares of industry-region pairs times time-varying occupation scores is uncorrelated with the demeaned error term. This would be the case if robotics inventions are indeed driven by the technology supply side and not demand side factors. One potential threat to identification would be if global robotics inventions over time are concentrated on tasks that are costly or difficult to offshore or unsafe for humans to perform and so there is more incentive to find ways to automate. An example of this could be tasks involving very large, heavy object that are expensive to move around, for example car chassis, or tasks involving dangerous procedures or handling chemicals, such as plastic moulding or metal casting. If this were the case then we might find that Spanish region-industry pairs with a high baseline employment share of occupations conducting these tasks, might, over time, experience both an increase in relevant global patenting and relatively little offshoring from Spain. This would lead to estimates of the impact of robots on offshoring that were biased downwards. Given we find a positive relationship, this should only serve to dampen our results.

Another possibility could be that international firms or research institutions have tried to invent robots specifically to automate the same occupations that Spanish firms have wanted to offshore. This could be the case if these are particularly labour intensive occupations

[21] We construct these measures ourselves, rather than using the measures constructed by Graetz and Michaels (2018), because their measures are constructed for the US Census occupational classification and we would need to combine multiple crosswalks to convert these to ISCO 68, or construct a new crosswalk ourselves, which would result in a loss of accuracy relative to conducting the hand-matching ourselves.

or occupations suitable to both automation and offshoring. If this were the case then we might expect that region-industry pairs with a high baseline employment share of occupations conducting these tasks, might, over time, experience both an increase in relevant robotics patenting and offshoring. If these changes occurred at the same time and within industry groups, then we might overestimate the impact of robot use on offshoring. Anecdotally, it does not appear that this is the case; as described above, many robotics inventions have been linked to robotics arms and robots are still incapable of many labour intensive tasks that are offshored. However, it remains a possibility and so we try to address this challenge in a few ways. By controlling for region-year and industry-group year fixed effects, we remove all but within-region over time and within-industry-group over time trends. We also add additional controls for factors that have made it easier to offshore certain tasks over time, that could have co-occurred with patenting. We control for global supply shocks that reflect the increased opportunities to offshore production to countries, such as China and Eastern Europe, via our Hummels et al. (2014) style instrument and also for changes in intermediate import tariffs set at the EU level that may have made it cheaper to offshore.

A final concern is around import competition. We have not explicitly included the role of import competition in our analysis so far, although this time period was also one of increased competition for Spanish firms, particularly from China. One common way of controlling for import competition in the literature is to use Autor et al. (2013)) style local labour market shift share instruments. In our specification we include region-year fixed effects, which would fully absorb such a control. Import competition would be a threat to our identification if it affected firms within the same industry group and region and influenced both global robotics patenting and Spanish firms' offshoring or firm performance at the same time. One way in which we are able to address this possibility is through controlling for exogenously set tariffs and we do so with our same-industry import tariff control. This control aims to soak up industry-time varying changes that may have influenced import competition through lowering trade costs.[22]

[22] One final additional concern could be around the validity of shift-share instruments. Recent literature stresses the importance of controlling for the shares used to construct the shift-share variables (see, for example, Borusyak et al. (2019)). In our specification, however, we include firm fixed effects and so this is not a concern; if we added such a control it would drop our of the regression because the shares are time-invariant.

6. Results

6.1 Baseline results

Table 5 presents the baseline results using the patent instrument. 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.[23] 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) displays results for the outcome variables relating to imports and multinational activity involving lower income countries. Starting to use robots has a substantial positive impact on imports from lower income countries. a positive impact on the intensity of imports from lower income countries and a positive impact on the number of affiliates in lower income countries. Robot use has no statistically significant effect on the share of imports from lower income countries, however, or on the share of affiliates in lower income countries.

These coefficients imply substantial impacts of robot adoption. The coefficient for imports from lower income countries implies that starting to use robots causes an approximately 13 fold increase in the value of imports. There are a few reasons why this value might be so high. This coefficient accounts for both the extensive margin and intensive margin of trade, which we explore in the next section. For firms switching from not importing at all from lower income countries to starting to do so (which we find to be the case), the percentage change will be large. In addition, our robot adoption variable takes only the valuss of zero or one and so a switch could imply anything from starting to use one robot to switching production to a fully automated system. If it is the latter we are mainly capturing, then we would expect large results. We further explore the impact of the intensive margin of automation in Section 6.5. We also try replacing the IHS transformation with alternatives in the Section 7.6, 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

[23] 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 5. BASELINE IV RESULTS

	IV FIXED EFFECTS REGRESSIONS 1990-2016				
	Panel (a): International outcomes involving lower income countries				
Dep variable:	Imports (1)	Import intensity (2)	Import share (3)	Affiliates (4)	Affiliate share (5)
Robot use	12.4***	0.049*	-0.14	0.49**	0.12
	(3.09)	(0.026)	(0.16)	(0.25)	(0.11)
First stage coef.	0.0051***	0.0051***	0.0049***	0.0041***	0.0041***
	(0.00077)	(0.00077)	(0.00076)	(0.00100)	(0.00100)
First stage F stat	43.5	43.5	40.5	17.1	17.1
Observations	37285	37256	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 (6)	Output (7)	Labour share (8)	Labour productivity (9)	TFP (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, 9 and 10 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.

firms to increase their number of affiliates in lower income countries by approximately 50%.

Panel (b) displays the results for the domestic outcome variables. We find that, when using this IV, starting to use robots raises employment, the value of goods and services produced, labour productivity and TFP and decreases the labour share. 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. Table **??** in Appendix B also includes this and all other results relating to TFP for Olley-Pakes TFP instead.

We also repeat these baseline results with weightings by baseline firm output. Table 22 in Appendix B 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. In addition, we repeat this analysis keeping only firms which remain in the sample for at least 5 years, finding that doing so barely affects the results, which we report in Table 19 in Appendix B.

Table 18 in Appendix B also presents the baseline results without instrumenting for robot use. These results suggest that without using an IV, within-firm switching into using robots is associated with an increase in the value of imports from lower income countries and the intensity of imports from lower income countries, higher employment, greater production of goods or services, higher labour productivity and higher TFP. There are two main differences between the OLS and IV results. First, the magnitude of the coefficients for OLS is far lower in all specifications. Second, for OLS there is no statistically significant relationship between robots and the number of developing country affiliates or the labour share. For the latter we provide a few guesses as to why this could be the case. It is plausible that firms that are looking to cut labour costs and so decreasing their labour share through means other than robots are then less likely to adopt robots, because they have already reduced labour costs through these means, such as outsourcing, hiring gig economy workers or investing in other forms of technology. Likewise, firms that have just opened affiliates abroad, particularly if for labour cost saving reasons, may be less interested in adopting robots at home. These possibilities would both bias coefficients in the OLS regressions towards zero. For the former, we also speculate that similar forces could be at play, biasing the other coefficients towards zero, such as firms that have already started offshoring to lower income countries being subsequently less likely to adopt robots.

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, lower income countries. Our results above in Table 5 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 lower income countries as well as the value of imports conditional on importing. Table 6 first displays results for the impact of robot use on a dummy variable for whether a firm imports from lower income countries, in Column (1) and whether it has affiliates in lower income countries in Column (2). For importing, the coefficient is statistically significant to the 5% level, showing that within-firm switching into using robots has

TABLE 6. EXTENSIVE MARGIN AND AFFILIATE ACTIVITIES

	IV FIXED EFFECTS REGRESSIONS 1990-2016					
	Extensive margin		Activities at main affiliate			
Dep variable:	Starts importing (1)	Opens affiliates (2)	Affiliate employment (3)	Adaptation & assembly (4)	Marketing & distribution (5)	Similar production (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.

a positive impact on whether a firm imports from lower income countries. Starting to use robots makes firms approximately 57% more likely to import from lower income countries. For opening affiliates, the coefficient is statistically significant to the 10% level, showing a weak relationship between using robots and opening affiliates in lower income 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 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 7 we display our baseline results firstly restricting the sample to only firms that started importing intensively from lower income countries prior to using robots and then using the full sample with interaction terms. As in section 4, we define importing intensively from lower income countries as being in the top 20% of the sample in terms of imports from lower income countries, equivalent to importing 1% or 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 lower income 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 lower income countries, the import intensity or on the extensive margin. Its only effect is to reduce the share of imports from lower income countries by approximately 0.39. These results could suggest that firms that were already importing intensively, upon adopting robots, do not change their imports from lower income countries, but start importing from high-income countries, meaning the lower income country share of imports declines.

Panel (b) displays the results when including the full sample but using the interaction term between a dummy variable for being a firm that imported intensively from lower income countries before adopting robots and robot use. 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 lower income countries depending on the sequencing of importing and robot adoption. 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. In Figure 21 we also show that these results hold if we instead define importing intensively as being in the top 20% within industries,

TABLE 7. SEQUENCING OF IMPORTING INTENSIVELY AND ROBOT USE

	IV FIXED EFFECTS REGRESSIONS 1990-2016			
	Panel (a): Only firms that import intensively first			
Dep variable:	Imports (1)	Import intensity (2)	Import share (3)	Starts importing (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 (5)	Import intensity (6)	Import share (7)	Starts importing (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. Importing intensively is defined as being in the top 20% of the sample in terms of import intensity from lower income countries, defined as the value of imports from lower income countries scaled by output. Panel (a) limits the sample to only firms that import intensively from lower income countries before adopting robots. Panel (b) looks at the interaction between robot use and whether a firm first imported intensively from lower income countries before adopting robots, or not. The dependent variables of 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.

or as the top 15% of the sample, although for the latter, for the limited sample regression, the significance of the result for the import share drops out.

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 5 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 8 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 are 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 robot use 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 around 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 around 80%. Meanwhile we find no effect of robot use on the number of administrative workers or non-graduates.

6.5 Intensive margin of automation

So far our results have focused on the extensive margin of robot adoption 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

TABLE 8. CHANGES TO EMPLOYMENT AND OPERATIONS IN SPAIN

	IV FIXED EFFECTS REGRESSIONS 1990-2016					
Dep variable:	Labour Costs	Change regular workers	Production	Clerical	Nongraduate	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.

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 9 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 lower income countries, the intensity of imports from lower income countries and the number of affiliates in lower income countries. In terms of magnitude, a 10% increase in the stock of industrial machinery for robot users increases imports from lower income countries by around 7%, the intensity of imports from lower income countries by around 0.03% and the number of affiliates in lower income countries by around 0.3%. 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.

TABLE 9. INTENSIVE MARGIN OF AUTOMATION

	IV FIXED EFFECTS REGRESSIONS 1990-2016				
	Panel (a): International outcomes involving lower income 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 $\times$ 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.

7. Robustness

7.1 Controlling for changes to world export supply

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 lower income 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 Section 3.5 we outlined a control variable similar to the world export supply instrument for offshoring used in Hummels et al. (2014), designed to encompass a firm's exposure to changes to the global supply side of offshoring that are external to Spain, but could potentially influence the firm's decision to offshore, for example, the rise of China as a global export hub or the rise of Bangladesh as a destination for apparel offshoring. This control variable is a plausibly exogenous determinant of offshoring and so we include it to ensure that our instrument for robot use is not in some way reflecting these global supply shocks, as opposed to only the technology supply side of robotics inventions.

Table 10 repeats the regressions in the baseline results table, also including this control. We see that this variable does have a strong impact on offshoring; in Columns 1-3 it is statistically significant, suggesting that firms that were initially importing from destinations that subsequently experienced an increase in their exports to other similar countries to Spain, saw an increase in their imports, import intensity and import share from lower income countries. This variable also has a positive impact on output and TFP and a negative impact on the labour share. Including this control has little effect on the coefficients for robot use, except to marginally increase the magnitude or significance of the coefficients for import value, import intensity, output, the labour share and TFP variables and marginally decrease the significance of the coefficient for the affiliates variable. These results generally suggest that omitting this control

TABLE 10. CONTROLLING FOR CHANGES TO WORLD EXPORT SUPPLY

	IV FIXED EFFECTS REGRESSIONS 1990-2016				
	Panel (a): International outcomes involving lower income countries				
Dep variable:	Imports (1)	Import intensity (2)	Import share (3)	Affiliates (4)	Affiliate share (5)
Robot use	13.4***	0.053**	0.042	0.50*	0.11
	(3.12)	(0.026)	(0.16)	(0.26)	(0.11)
Offshoring instrument	1.12***	0.0052***	0.20***	0.0068	-0.0096
	(0.13)	(0.0011)	(0.0072)	(0.019)	(0.0089)
First stage F stat	44.2	44.2	41.2	15.8	15.8
Observations	37285	37256	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 (6)	Output (7)	Labour share (8)	Labour productivity (9)	TFP (10)
Robot use	0.59**	2.54***	-0.51***	1.54***	3.15***
	(0.27)	(0.46)	(0.11)	(0.33)	(0.55)
Offshoring instrument	-0.014	0.054***	-0.022***	0.029*	0.098***
	(0.010)	(0.019)	(0.0053)	(0.015)	(0.033)
First stage F stat	37.1	40.8	36.3	35.4	38.3
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, 9 and 10 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 offshoring instrument is the firm baseline import share & IO table weighted value of industry level exports from the world to the four EU countries with the closest GDP per capita to Spain, transformed by IHS. These results are not weighted. Standard errors are robust to heteroskedasticity and serial correlation at the industry-region-year level.

for external factors that made firms more likely to offshore has not biased our results for the impact of automation, except perhaps very slightly downwards.

7.2 Controlling for import tariff changes

In the context of offshoring, a further factor we might be particularly concerned about is the fall in import tariffs that may have reduced the cost of offshoring to lower income 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

TABLE 11. CONTROLLING FOR IMPORT TARIFF CHANGES

	IV FIXED EFFECTS REGRESSIONS 1990-2016				
	Panel (a): International outcomes involving lower income 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 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 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, 9 and 10 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.

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 11. Adding these 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.

TABLE 12. EXCLUDING THE FINANCIAL CRISIS

	IV FIXED EFFECTS REGRESSIONS 1990-2016 EXCLUDING 2007-2010				
	Panel (a): International outcomes involving lower income 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.

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 12 repeats the analysis in Table 5 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 13 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

TABLE 13. IFR INSTRUMENT FOR ROBOT ADOPTION

	IV FIXED EFFECTS REGRESSIONS 1990-2016				
	Panel (a): International outcomes involving lower income countries				
Dep variable:	Imports (1)	Import intensity (2)	Import share (3)	Affiliates (4)	Affiliate share (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 (6)	Output (7)	Labour share (8)	Labour productivity (9)	TFP (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 IFR 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 14. EXCLUDING THE AUTOMOTIVE SECTOR

	IV FIXED EFFECTS REGRESSIONS 1990-2016				
	Panel (a): International outcomes involving lower income 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.

other outcome variables. The coefficient for the value of imports from lower income countries is now slightly less statistically significant at only 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. We can also use this instrument to conduct a GMM difference test (a.k.a. C test) for the orthogonality of our two instruments. We are able to reject the null for both instruments, supporting their validity. Taken together these results generally suggest that the key results for the impact of robot use on imports from lower income 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

TABLE 15. ALTERNATIVE SPECIFICATIONS FOR IMPORTS REGRESSIONS

IV FIXED EFFECTS REGRESSIONS 1990-2016				
Dep variable:	Imports from lower income countries			
Specification:	IHS (1)	ln(1+x) (2)	PPML (3)	ln(x) (4)
Robot use	12.4*** (3.09)	11.9*** (2.95)	11.6** (4.86)	0.62 (1.36)
First stage F stat	43.5	43.5	-	10.6
Observations	37285	37285	37285	8464
Firm FE	Y	Y	Y	Y
Year FE	N	N	N	Y
Region-year FE	Y	Y	Y	N
Industry Group-Year FE	Y	Y	Y	N

Notes: This table presents estimates of the relationship between the dummy variable for firm use of robots and the value of imports from lower income countries, with the specifications in columns 1-4. 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 1,2 and 4 are robust to heteroskedasticity and serial correlation at the industry-region-year level. For column 3 we use the control-function method to estimate the IV-PPML model and bootstrap the standard errors.

sector from our analysis. Table 14 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 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 lower income countries was very high and the estimation problem of having many firm-year observations with zero imports from lower income countries. We hence also try repeating the analysis for this outcome variable 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 15 displays the results. We find that trying these two alternative 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 lower income countries is inflating our coefficients, although the coefficient still remains very high in magnitude at 11.6.

We also include the results taking only the log. All observations with zero imports from lower income countries then drop out of the sample, resulting in a far smaller sample size and a weak first stage. The result is not significant for this logged specification, further suggesting that when we focus only on changes to importing amongst firms already importing from lower income countries, there is less of an impact of robots, perhaps because an important part of the effect is the extensive margin of switching into importing.

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 lower income 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, lower income 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, lower income 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 global supply shocks that made it easier to offshore production, 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 lower income 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 lower income countries, suggesting that automation does, to some degree, shift economic activity away from lower income 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 lower income 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, lower income 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 lower income countries, particularly after the Financial Crisis, through the channel of firms that imported intensively before automating reducing their lower income country import share, we do not find any aggregate negative effects. Firms that imported intensively before automating did not decrease their absolute value of imports from lower income countries. For the full sample the total value of imports and the import intensity from lower income 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.

References

Acemoglu, Daron and David Autor, “Skills, Tasks and Technologies: Implications for Employment and Earnings,” in “Handbook of Labor Economics,” Vol. 4, Elsevier, 2011, pp. 1043–1171.

_ and Pascual Restrepo, “The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment,” *American Economic Review*, June 2018, *108* (6), 1488–1542.

_ and _ , “Robots and Jobs: Evidence from US Labor Markets,” *Journal of Political Economy*, August 2019.

_ , Claire LeLarge, and Pascual Restrepo, “Competing with Robots: Firm-Level Evidence from France,” Working Paper 26738, National Bureau of Economic Research February 2020.

Aghion, C. Antonin, S. Bunel, and X. Jaravel, “What Are the Labor and Product Market Effects of Automation? New Evidence from France,” 2020.

Antràs, Pol, “Conceptual Aspects of Global Value Chains,” *World Bank Economic Review*, 2020.

_ and Stephen R. Yeaple, “Multinational Firms and the Structure of International Trade,” in “Handbook of International Economics,” Vol. 4, Elsevier, 2014, pp. 55–130.

Artuc, Erhan, Luc Christiaensen, and Hernan Jorge Winkler, “Does Automation in Rich Countries Hurt Developing Ones? : Evidence from the U.S. and Mexico,” Technical Report 8741, The World Bank February 2019.

_ , Paulo S. R. Bastos, and Bob Rijkers, “Robots, Tasks and Trade,” Technical Report 8674, The World Bank December 2018.

Autor, David, David Dorn, Lawrence F. Katz, Christina Patterson, and John Van Reenen, “The Fall of the Labor Share and the Rise of Superstar Firms,” *Quarterly Journal of Economics*, 2020, *135* (2).

Autor, David H., David Dorn, and Gordon H. Hanson, "The China Syndrome: Local Labor Market Effects of Import Competition in the United States," *American Economic Review*, October 2013, *103* (6), 2121–2168.

Baldwin, Richard and Rikard Forslid, "Globotics and Development: When Manufacturing is Jobless and Services are Tradable," Working Paper 26731, National Bureau of Economic Research February 2020.

Bernard, Andrew B., J. Bradford Jensen, Stephen J. Redding, and Peter K. Schott, "The Margins of US Trade," *American Economic Review*, May 2009, *99* (2), 487–493.

_, Jonathan Eaton, J. Bradford Jensen, and Samuel Kortum, "Plants and Productivity in International Trade," *American Economic Review*, September 2003, *93* (4), 1268–1290.

Bernard, Andrew B, Teresa C Fort, Frederic Warzynski, and Valerie Smeets, "Heterogeneous Globalization: Offshoring and Reorganization," 2019, p. 39.

Bessen, James E., Maarten Goos, Anna Salomons, and Wiljan Van den Berge, "Automatic Reaction - What Happens to Workers at Firms that Automate?," SSRN Scholarly Paper ID 3328877, Social Science Research Network, Rochester, NY January 2019.

Blinder, Alan S. and Alan B. Krueger, "Alternative Measures of Offshorability: A Survey Approach," *Journal of Labor Economics*, 2013, *31* (2), S97–S128.

Borusyak, Kirill, Peter Hull, and Xavier Jaravel, "Quasi-Experimental Shift-share Research Designs," 2019.

Bustos, Paula, "Trade Liberalization, Exports, and Technology Upgrading: Evidence on the Impact of MERCOSUR on Argentinian Firms," *American Economic Review*, February 2011, *101* (1), 304–340.

Chen, Cheng and Claudia Steinwender, "Import Competition, Heterogeneous Preferences of Managers, and Productivity," Working Paper 25539, National Bureau of Economic Research February 2019. Series: Working Paper Series.

Faber, Marius, "Robots and reshoring: Evidence from Mexican local labor markets," Technical Report 2018/27, Faculty of Business and Economics - University of Basel October 2018. Publication Title: Working papers.

Feenstra, Robert C. and Gordon H. Hanson, "The Impact of Outsourcing and High-Technology Capital on Wages: Estimates For the United States, 1979–1990," *Q J Econ*, August 1999, *114* (3), 907–940.

Fort, Teresa C., "Technology and Production Fragmentation: Domestic versus Foreign Sourcing," *Rev Econ Stud*, April 2017, *84* (2), 650–687.

Graetz, Georg and Guy Michaels, "Robots at Work," *The Review of Economics and Statistics*, July 2018, *100* (5), 753–768.

Hallward-Driemeier, Mary and Gaurav Nayyar, "Have Robots Grounded the Flying Geese?: Evidence from Greenfield FDI in Manufacturing," SSRN Scholarly Paper ID 3510400, Social Science Research Network, Rochester, NY December 2019.

Hallward-Driemeier, Mary C. and Gaurav Nayyar, *Trouble in the Making?: The Future of Manufacturing-Led Development* 2017.

Honnibal, Matthew and Mark Johnson, "An Improved Non-monotonic Transition System for Dependency Parsing," in "Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing" Association for Computational Linguistics Lisbon, Portugal September 2015, pp. 1373–1378.

Hummels, David, Rasmus Jørgensen, Jakob Munch, and Chong Xiang, "The Wage Effects of Offshoring: Evidence from Danish Matched Worker-Firm Data," *American Economic Review*, June 2014, *104* (6), 1597–1629.

IFR, "World Robotics 2019 Edition," Technical Report 2019.

Melitz, Marc J., "The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity," *Econometrica*, 2003, *71* (6), 1695–1725.

Miller, George A., "WordNet: a lexical database for English," *Commun. ACM*, November 1995, *38* (11), 39–41.

Pedemonte, Mathieu, Tara Vishwanath, and Roman D Zarate, "Trade, Robots and Automation: The Impact of US Robots on Labor Outcomes in Developing Countries," 2019, p. 31.

Song, Jae, David J. Price, Fatih Guvenen, Nicholas Bloom, and Till von Wachter, "Firming Up Inequality," *Q J Econ*, February 2019, *134* (1), 1–50.

Steinwender, Claudia, "Real Effects of Information Frictions: When the States and the Kingdom Became United," *American Economic Review*, March 2018, *108* (3), 657–696.

Webb, Michael, "The Impact of Artificial Intelligence on the Labor Market," *SSRN Journal*, 2019.

Appendices

A. Additional figures

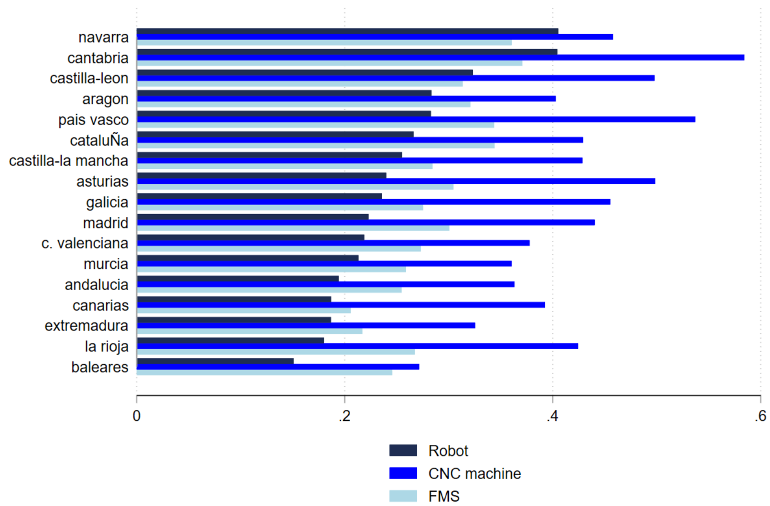


Figure 8: Technology use by region

Notes: This figure displays the share of firms using the three technologies, over all time periods, by Spanish region included in the ESEE data.

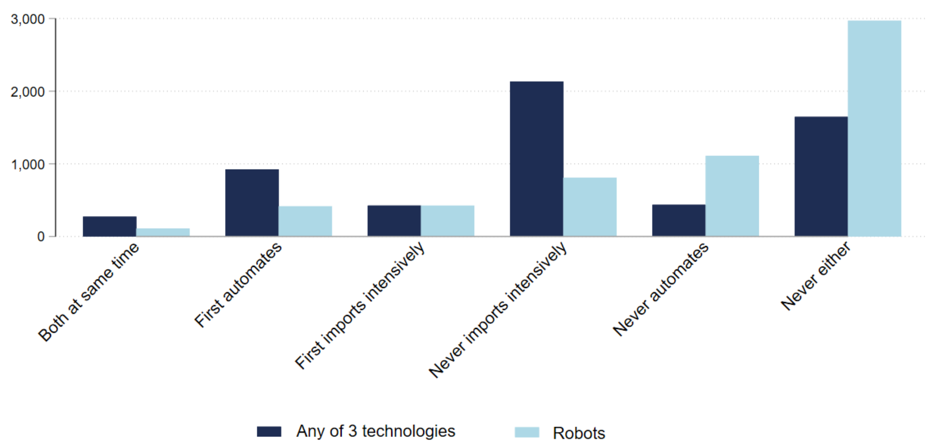


Figure 9: Sequencing of automation and importing intensively from lower income countries

Notes: This figure displays the number of firms by the sequencing of automation and importing intensively from lower income countries. Importing intensively is defined as being in the top 20% of the industry in terms of import intensity from lower income countries.

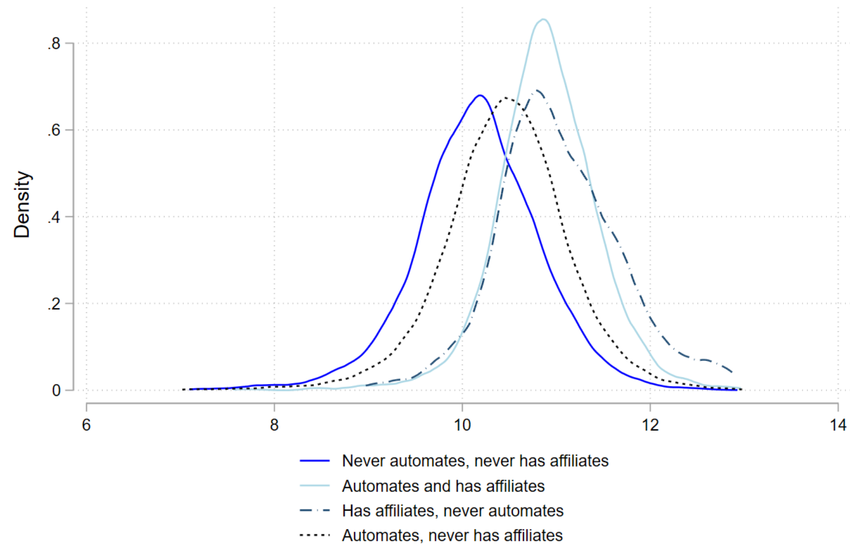
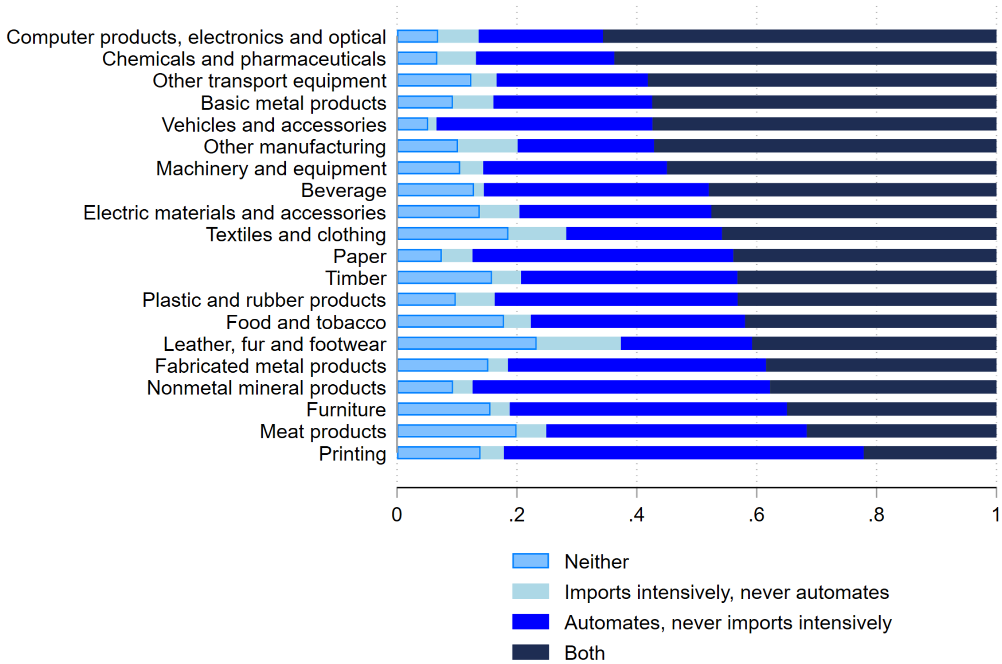
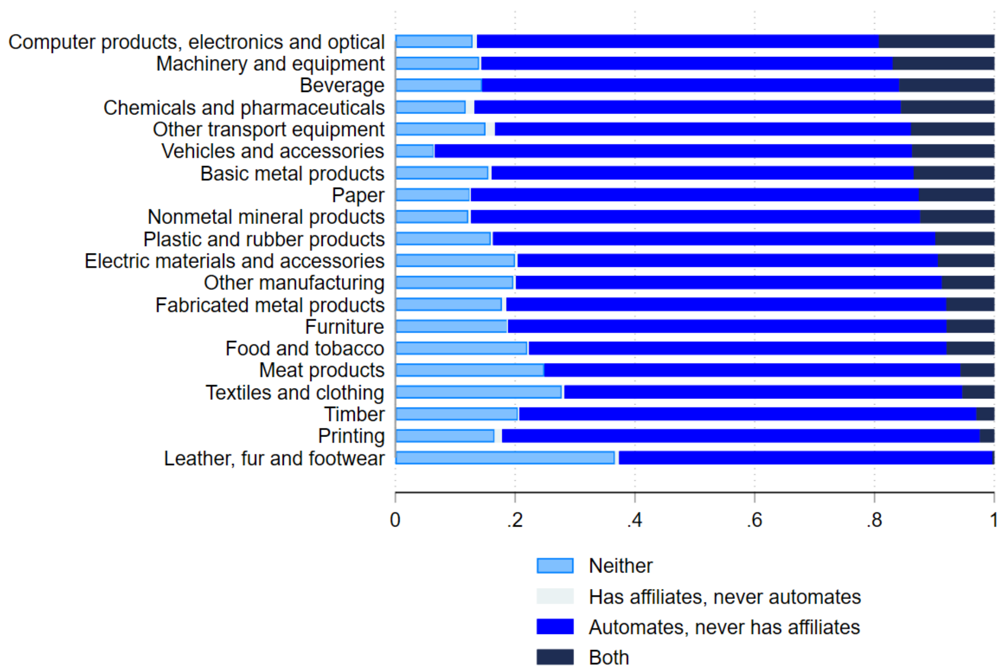


Figure 10: Labour productivity distribution by automation and less dev MNC status

Notes: This figure displays the distribution of the log of value added per worker across firms depending on whether they ever have affiliates in lower income countries or ever use robots, neither or both.



(a) Importing intensively from less dev. countries



(b) Affiliates in less dev. countries

Figure 11: Automation, importing intensively or affiliates in lower income countries, by industry

Notes: Panel (a) displays the share of firms by whether they ever import intensively from lower income countries, defined as being in the top 20% of the sample or whether they ever use robots, neither or both, by industry. Panel (b) displays the same in terms of whether they ever have affiliates in lower income countries.

B. Additional tables

TABLE 16. CORRELATION BETWEEN TECHNOLOGY USE

	Robots	FMS	CNC Machines
Robots	1		
FMS	0.2261	1	
CNC Machines	0.3407	0.177	1

Notes: This table displays the correlation coefficients between the three dummy variables for use of robots, FMS and CNC Machines.

TABLE 17. ISCO 68 CODES WITH HIGHEST & LOWEST PATENT SCORES

Most exposed	Least exposed
97: Material-Handling & Related Equipment Operators, Dockers & Freight Handlers	14: Workers in Religion
98: Transport Equipment Operators	20: Legislative Officials & Government Administrators
84: Machinery Fitters, Machine Assemblers & Precision Instrument Makers	11: Accountants
54: Maids and Related Housekeeping Service Workers NEC	12: Jurists
96: Stationary Engine and Related Equipment Operators	15: Authors, Journalists & Related Writers

Notes: This table displays the top 5 and bottom 5 most and least robot exposed occupations at ISCO 68 level using the patent-derived exposure measure.

TABLE 18. RESULTS WITHOUT IV

	FIXED EFFECTS REGRESSIONS 1990-2016				
	Panel (a): International outcomes involving lower income countries				
Dep variable:	Imports (1)	Import intensity (2)	Import share (3)	Affiliates (4)	Affiliate share (5)
Robot use	0.38***	0.0021***	-0.0036	-0.0026	0.00091
	(0.083)	(0.00070)	(0.0052)	(0.0061)	(0.0029)
Observations	46435	46399	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 (6)	Output (7)	Labour share (8)	Labour productivity (9)	TFP (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.

TABLE 19. BASELINE RESULTS EXCLUDING FIRMS WITH <5 YEAR OBS

	IV FIXED EFFECTS REGRESSIONS 1990-2016				
	Panel (a): International outcomes involving lower income countries				
Dep variable:	Imports (6)	Import intensity (7)	Import share (8)	Affiliates (9)	Affiliate share (10)
Robot use	12.4***	0.049*	-0.14	0.49**	0.12
	(3.11)	(0.026)	(0.17)	(0.25)	(0.11)
First stage F stat	43.1	43.1	40.1	17.1	17.1
Observations	37249	37220	37477	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 (1)	Output (2)	Labour share (3)	Labour productivity (4)	TFP (5)
Robot use	0.60**	2.50***	-0.49***	1.51***	3.06***
	(0.27)	(0.46)	(0.11)	(0.33)	(0.53)
First stage F stat	36.5	39.7	35.8	34.9	39.1
Observations	35896	37333	35831	35509	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. Firms with less than five time series observations are excluded. 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 20. BASELINE IV RESULTS: WEIGHTED

	IV FIXED EFFECTS REGRESSIONS 1990-2016				
	Panel (a): International outcomes involving lower income 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, 9 and 10 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.

TABLE 21. CHANGING THRESHOLDS FOR IMPORT INTENSITY

	IV FIXED EFFECTS REGRESSIONS 1990-2016							
	Top 20% within industries				Top 15% of sample			
	Panel (a): Only firms that import intensively first							
Dep variable:	Imports	Import intensity	Import share	Starts importing	Imports	Import intensity	Import share	Starts importing
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Robot use	-0.65	0.051	-0.50**	-0.53*	0.58	0.036	-0.0086	-0.0027
	(3.48)	(0.055)	(0.22)	(0.30)	(4.54)	(0.074)	(0.26)	(0.34)
First stage F stat	22.4	22.2	20.2	20.2	14.1	14.0	13.1	13.1
Observations	5218	5209	5272	5272	4268	4259	4313	4313
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Region-year FE	N	N	N	N	N	N	N	N
Industry Group-Year FE	N	N	N	N	N	N	N	N
	Panel (B): Full sample with first importing intensively interaction							
Dep variable:	Imports	Import intensity	Import share	Starts importing	Imports	Import intensity	Import share	Starts importing
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Robot use	20.1***	-0.015	-0.33	1.14***	15.8***	-0.0069	-0.29	0.87***
	(5.90)	(0.044)	(0.26)	(0.43)	(4.36)	(0.036)	(0.21)	(0.33)
Robot * first imp intensively	-18.0***	0.046	0.22	-1.11***	-13.2***	0.046	0.24	-0.78***
	(5.14)	(0.037)	(0.22)	(0.37)	(3.63)	(0.028)	(0.17)	(0.27)
First stage F stat	12.2	12.1	12.0	12.0	17.6	17.5	17.2	17.2
Observations	37285	37256	37517	37517	37285	37256	37517	37517
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Region-year FE	Y	Y	Y	Y	Y	Y	Y	Y
Industry Group-Year FE	Y	Y	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 1-8. columns 1-4 define importing intensively as being in the top 20% within the same industry in terms of import intensity from less developed countries. Columns 5-8 define it as being in the top 15% of the sample. 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.

TABLE 22. OLLEY-PAKES TFP

IV FIXED EFFECTS REGRESSIONS 1990-2016								
Instrument:	Patent							IFR
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Robot use	2.65***	2.97***	2.72***	2.60***	2.78***	3.34***		1.40***
	(0.48)	(0.60)	(0.50)	(0.46)	(0.54)	(0.76)		(0.32)
Log machinery stock							0.17***	
							(0.031)	
First stage F stat	39.1	30.5	38.3	42.0	34.7	23.7	38.8	48.0
Observations	32025	32025	32025	31981	25998	30443	30716	39184
Weighting	N	Y	N	N	N	N	N	N
World export supply control	N	N	Y	N	N	N	N	N
Tariff control	N	N	N	Y	N	N	N	N
Excluding 2007-2010	N	N	N	N	Y	N	N	N
Excluding automotive	N	N	N	N	N	Y	N	N

Notes: This table presents estimates of the relationship between the dummy variable for firm use of robots and the log of TFP estimated using the Olley-Pakes method, instead of Levinson-Petrin, for all of the main specifications and robustness checks. All regressions also include firm, region-year and industry group-year fixed effects. Standard errors are robust to heteroskedasticity and serial correlation at the industry-region-year level.

C. Additional definitions

EU and OECD membership over time

The following countries were members of either the OECD or the EU in 1990: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Japan, Luxembourg, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, Turkey, UK, US. These countries collectively account for 64% of Spain's total imports over the period of 1990-2016, according to UNCOMTRADE data.

The following countries switch status to join the group of OECD & EU countries during our sample period. Table 23 displays the countries that switched into this group during the sample, recorded by the year when they first switched into this group and the organisation they joined. These countries collectively account for 6% of Spain's imports over the period of 1990-2016. The countries in this group accounting for the largest trade volume are Mexico, with 1.3% of all imports from 1990-2016 and South Korea, with 0.9% of all imports.

TABLE 23. COUNTRIES THAT JOIN OECD & EU DURING SAMPLE PERIOD

Year	OECD	EU
1994	Mexico	
1995	Czech Republic	
1996	Hungary, Korea, Poland	
2000	Slovak Republic	
2004		Cyprus, Estonia, Latvia, Lithuania, Malta, Slovenia
2007		Bulgaria, Romania
2010	Chile, Israel	
2013	Croatia	

Notes: This table displays the countries that switched from the 'lower income country' group into the OECD & EU group during our sample, recorded by the date when they first joined either of these groups and the group they first joined. .