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

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Abstract

We use a rich dataset of Spanish manufacturing firms from 1990 to 2016 to shed new light on how automation in a high-income country affects trade and multinational activity involving lower-income countries. We exploit supply-side improvements in the capabilities of robots, as described in the text of robotics patents, that made it become technologically feasible over time to automate some tasks and not others. We show that, contrary to the assertion that automation in high-income countries will cause the reshoring of production, 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 adoption caused firms to expand production and increase labour productivity and TFP. For firms that had not yet offshored production to lower-income countries, robot adoption caused them to start newly doing so. By contrast, for firms that were already offshoring to lower-income countries, robot adoption had no impact on their offshoring but decreased their share of imports sourced from lower-income countries. We show that these findings can be explained in a framework that incorporates firm heterogeneity, the choice between automation, offshoring and performing tasks at home and where automation and offshoring both involve upfront fixed costs, such that their sequencing matters.

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

JEL codes: F12, F16, J23, J24

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1. Introduction

Recent technical advances in robotics and machine intelligence have spurred a new wave of research into the consequences of automation and, 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); Dauth et al. (2017)). 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 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 is attracting growing attention among policymakers: that automation might substitute for labour in lower-income countries, reducing the future scope for manufacturing-led development in parts of the world that have yet to industrialise and resulting in 'deglobalisation'.[1] The emergence of global supply chain-enabled manufacturing-led development has been an unrivalled force for poverty reduction. Of the 1.2 billion people that were lifted out of poverty between 1990 and 2015, 93% came from a select group of 7 countries that became heavily integrated in global supply chains over this period.[2] This question therefore has important implications, yet we are far from a satisfactory knowledge base, theoretical or empirical, about how automation affects trade patterns, or even how advances in labour-replacing technologies over the past three decades have impacted trade and global supply chains.

A key part of understanding the relationship between technological advances that make it easier, or cheaper, to automate production stages, and offshoring, is to consider firm level decisions about their supply chains and technology adoption. Manufacturers increasingly have 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

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

[2] These countries are China, India, Korea, Mexico, Poland, Indonesia and Thailand. 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

benefits. Existing research has tended to study automation at the industry or economy-wide level, missing out on these key firm decisions. To date there is, in fact, remarkably 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 an uncommon 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 are on average around twice as large, have around 60% higher TFP, export and import nearly four times more and are around 10% more likely to be a multinational than other firms in the same narrowly defined industry, region and year.

We find that prior to having adopted these technologies, firms that will adopt them in the future already import more and have more affiliates in all regions, including lower-income countries, but source a lower share of their imports from lower-income countries. This gap is then wider, in any time period, between firms that have already 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 less developed countries as vice versa. Firms that either automate, or offshore to lower-income countries, are more productive than firms that don't do either, but the most productive firms in the sample, in fact, both automate and offshore.

To guide empirical work, we incorporate a simple task-based framework similar to that in Acemoglu and Restrepo (2018c) into a model with Melitz (2003) style firm heterogeneity. Firms have the option to conduct tasks at home, offshore them or automate them. 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, but offering a marginal cost reduction. This results in productivity cutoffs for both automation and offshoring and only the most productive firms engage in both. The impact of automation then depends on whether the firm was already offshoring or not. For firms that were already offshoring, automation displaces tasks from offshore labour. For firms that were not offshoring, automation displaces tasks from home labour. For both, automation reduces production costs, generating a productivity effect, whereby automation allows firms to expand and demand more labour at home or abroad for non-automatable tasks. This productivity effect can also induce non-offshoring firms to start offshoring non-automatable tasks by enabling them to afford the fixed cost of offshoring. Automation also causes between-firm reallocation to the more productive firms that can afford the fixed cost of automation.

To evaluate the causal impact of automation on trade and multinational activity, we exploit robotics inventions that made it become technically feasible, over time, to automate some tasks and not others. We follow Webb (2019) and use the text from patent titles to identify the overlap between the tasks that robotics inventions are designed to conduct and the tasks conducted by different occupations. This allows us to construct time-varying measures of exposure to technological advances in robotics. Our motivation is that many technological developments in robotics stem from research conducted at universities and breakthroughs are often driven by advances in complementary technologies in other fields. These supply-side advances in the technological capabilities of robots are plausibly exogenous to the Spanish firms that are subsequently faced with the commercial availability of some specific types of robots.

Using this instrument we show that, for the full sample, robot adoption in Spain caused firms to increase their value of imports from, and the number of affiliates in, lower-income countries. Robot adoption 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. We find that robot adoption 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 adoption 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. These results suggest that the within-firm positive productivity effect of robot adoption outweighs the displacement effect in terms of its impact on imports and multinational activity with lower-income countries.

Consistent with the theoretical framework, we find that the sequencing of robot adoption and offshoring has important consequences for the impact of robot adoption. When we focus on firms that were importing intensively from lower-income countries before they started to use robots, we find that 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, 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 adoption had 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 for the full sample the net impact of robot adoption on imports from lower-income countries is positive.

We demonstrate that our key empirical results hold after controlling for global supply side shocks that have made offshoring cheaper and easier, import tariff changes during this period, excluding the time period of the Global Financial Crisis, excluding the automotive sector and controlling for lagged multinational status and lagged TFP. For comparison, we also construct an additional instrument for robot adoption 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.

This research adds a number of new insights to the existing, nascent literature on how automation in high income countries affects trade and FDI to lower-income ones. There are a small number of papers using IFR industry-level robot sales data to study how exposure to robot adoption affects country-industry trade flows and 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. A few other papers, however, that focus only on trade between the US and Mexico, find negative effects of automation. Pedemonte et al. (2019), Artuc et al. (2019) and Faber (2018) all use data on employment or exports in Mexican local labour markets, finding that exposure to increased robot penetration in the US, as measured using the IFR data, reduces exports from Mexico to the US or employment in Mexico.

While these papers all rely on industry-level robot sales data, we are able to provide more granular evidence using data on robot adoption at the firm level, mitigating the concern that industry-level robot penetration may be correlated with other industry characteristics or shocks. Our results at the firm-level, and with an alternative identification strategy that relies on plausibly exogenous variation in robotics patents, generally support the findings of the former two papers that the net impact of robot adoption on imports from lower-income countries is a positive one. We also provide empirical evidence and a theoretical framework to explain some of the firm dynamics that could be underpinning these positive industry-level results: 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.

Our research also offers some hints as to why negative results of the latter set of papers might hold, despite the other cross-country studies finding a positive relationship. In our paper we found that the impact of automation differed depending on whether firms first automated or first offshored production. If the sample comprised of more firms that offshored first, however, we might expect a decrease in the share of imports from lower-income countries for the full sample. Additionally, our modelling framework suggests that firms that don't automate could lose market share to those that do, and, in our data 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 empirical 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), Aghion et al. (2020), Humlum (2020) and Koch et al. (2019) that automation induces within-firm scale and productivity effects.

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 empirical literature studying the effects of robots on labour markets (Acemoglu and Restrepo, 2018c, 2019; Graetz and Michaels, 2018; Dauth et al., 2017) and theoretical literature modelling the effects of automation. We build upon the task-based automation modelling frameworks of Acemoglu and Restrepo (2018c), Acemoglu and Restrepo (2018b) and Acemoglu and Restrepo (2018a), which incorporate insights from the foundational work of Acemoglu and Autor (2011), Acemoglu and Zilibotti (2001) and Zeira (1998).

We also build upon frameworks in the international trade literature on heterogeneous firms, task-based offshoring and the interaction between technology adoption and trade (e.g. Melitz (2003), Grossman and Rossi-Hansberg (2008), Antràs and Yeaple (2014) and Bustos (2011)). Additionally, we contribute 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 offer a new angle on how labour replacing technologies shape global trade.

Finally, this paper contributes to an expanding literature on superstar firms and on the reasons for the decline in the labour share (e.g. Autor et al. (2020) and Song et al. (2019)). We add evidence to the debate on whether firms that automate already have lower labour shares or whether automation causes them to decrease their labour shares, showing that for Spanish manufacturing firms both channels were at play. We also offer evidence of a further mechanism through which automation may cause the rise in superstar firms: automation further reinforces existing productivity differentials through allowing firms that automate to further expand and become more productive by starting to offshore tasks that cannot be automated.

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

2. Data

2.1 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.[3] 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.[4] A description of these technologies is as follows:

1. **Robots:** 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 in the survey questionnaire. However, given the survey covers manufacturing firms up to 2016, when collaborative robots were less widely commercially available, we assume these are likely to be primarily industrial robots.

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

[4] The dataset also asks about firm use of Computer Aided Design/Computer Aided Manufacturing (CAD/CAM), but in our analysis we don't include CAD/CAM as CAD/CAM is a process and software that is typically combined with CNC machines, where CNC machines are the machinery that conducts the task.

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.

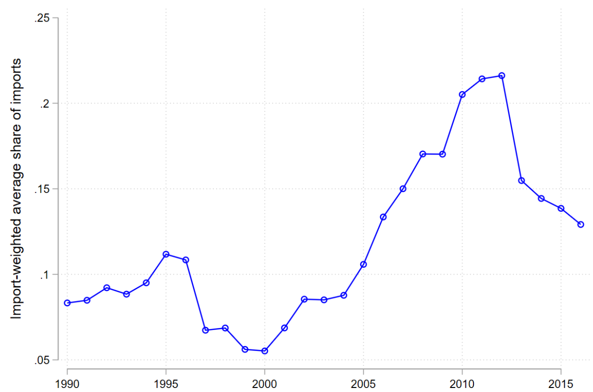
Figure **??** displays the share of firms using these technologies over time and Figure 5 in Appendix A displays the share using these technologies on average across all years by industry.[5] There are 20 industries in the ESEE data using the Spanish NACECLIO classification system, which is based on 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 14 in Appendix B we also display the correlation between use of 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.

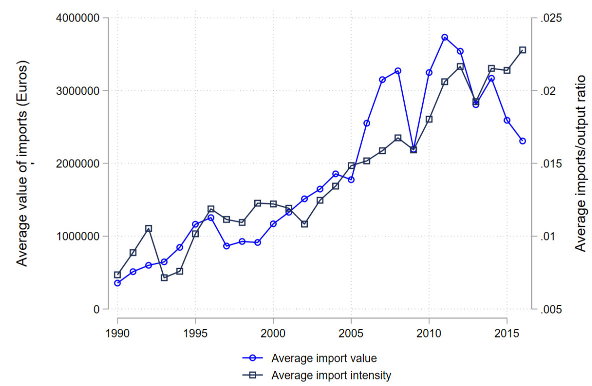
Trade and multinational activity variables: The key trade-related variables we use are the value of imports and breakdown of imports by region. Firms provide exports and imports broken down into region groups: the EU, OECD countries excluding the EU, Latin America and the Rest of World. We combine the 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 and their aggregate

[5] In Appendix A, Figure 6 also displays technology adoption by region.

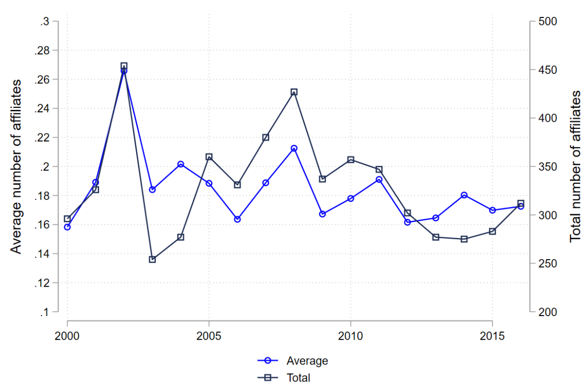
[6] These industries are meat related products; food and tobacco; beverage; textiles and clothing; leather, fur, and footwear; timber; paper; printing and publishing; chemicals; plastic and rubber products; nonmetal mineral products; basic metal products; fabricated metal products; industrial and agricultural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



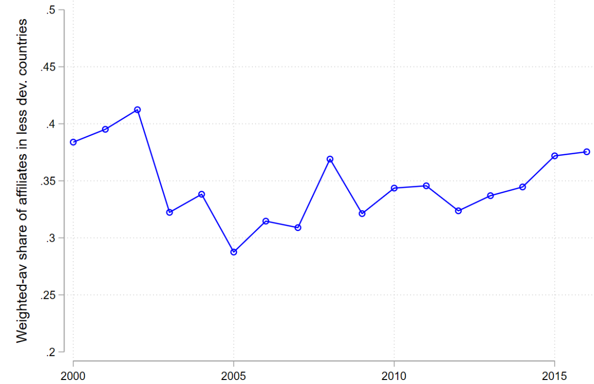
(a) Import share from less dev. countries



(b) Value of imports & import intensity



(c) Affiliates in less dev. countries



(d) Share of affiliates in less dev. countries

Figure 1: 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.

import shares in Appendix C. Membership of the EU and OECD changed slightly over time and we document these changes in Table 25 in Appendix C.[7]

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 categorise a firm as a multinational if it has at least one foreign affiliate.

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.

Offshoring could occur through unrelated party transactions or through related party transactions from foreign affiliates. We therefore also consider the impact of automation on the firm's number of affiliates in lower-income countries. [8]

[7]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.

[8]There are a number of reasons a firm might open affiliates abroad and only one of these is vertical specialisation

Figure 1 displays the key trade and multinational activity variables over time. Between 1990 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.[9] 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 7(a) in Appendix 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 7(b) in Appendix A 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

or providing inputs to the firm in Spain, which would be a proxy for offshoring. Most notably, opening a foreign affiliate in a lower-income country may be motivated by the desire to replicate the production processes in different countries to save on transportation costs or jump over tariffs. We therefore also consider the primary purpose of multinational affiliates.

[9]The same holds for the total value of imports from lower-income countries across all firms included in the data.

Files from EUKLEMS.[10] 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.[11] 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.[12] 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.[13] Figure **??** displays the evolution of these variables over the sample period. Table 1 displays the summary statistics for the key variables used in the analysis.

2.2 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

[10] http://www.euklems.net/

[11] This is calculated as the sum of the following items: Full-time regular personnel, 1/2 of the part-time regular personnel and the average number of temporary workers.

[12] 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

[13] 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.

population. We choose the 1981 sample because we are studying the impact of automation on offshoring and thus want the employment composition before offshoring began on a large scale. Ideally we would like to use the full sample of employment by industry, region and occupation, but this does not exist for Spain at a detailed enough level of disaggregation. The Census of Housing and Population is the most comprehensive data source on employment in these three dimensions.

2.3 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.[14] The fields used are the title, abstract, and CPC codes, as described further below. The O*NET database, produced by the US Department

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

of Labor, is also used as the source of information on occupations. O*NET describes 964 occupations. A set of tasks is listed for each occupation, described in natural language. Each task is also given scores that indicate its importance and frequency in the occupation. These scores are used to weight tasks within occupations. The method for constructing patent-occupation text similarity is outlined in Section 5.

2.4 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.

2.5 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.[15] We outline the construction of this control variable in Appendix C.

2.6 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

[15] These countries are Italy, Portugal, Slovenia and the Czech Republic.

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.

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 outline the construction of these variables in Appendix C.

3. Which firms automate?

We begin by documenting the characteristics of firms that use robots, FMS and CNC machines over time. 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

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.

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.

3.1 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:

$$X_i = \alpha + \beta \text{Technology}_i + \gamma \text{Industry}_i + \theta \text{Region}_i + \epsilon_i \tag{1}$$

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 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.

3.2 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:

$$X_i = \alpha + \beta \text{FutureTechnology}_i + \gamma \text{Industry}_i + \theta \text{Region}_i + \epsilon_i \tag{2}$$

where X_i is the outcome of interest for firm i, $\text{FutureTechnology}_i$ is a dummy variable for firm use at any point in the future recorded in the data of one of the technologies: robots, CNC

[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.

machines or FMS, Industry_i is firm i's 2 digit industry and Region_i is the Spanish autonomous community where firm i is headquartered. 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.

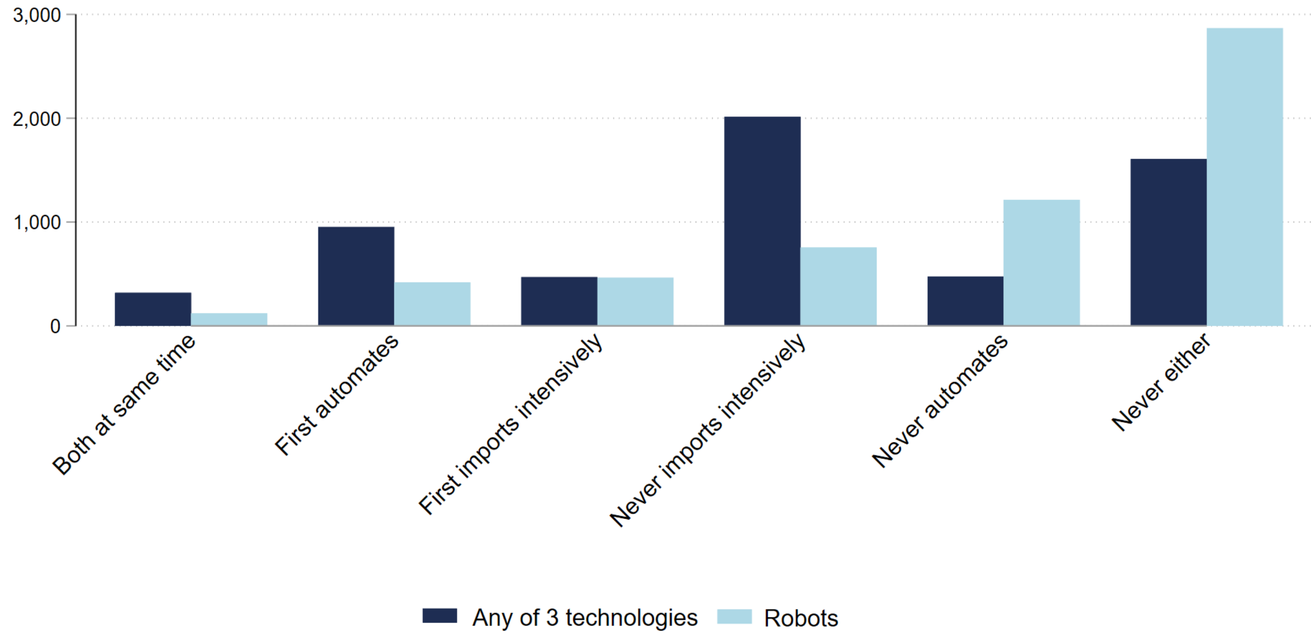


Figure 2: Sequencing of automation and importing intensively from lower-income countries

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.

3.3 Which comes first?

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 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 2 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.

3.4 Productivity of firms that automate, import and have affiliates

In Figure 3 we display the productivity distribution of firms that automate, firms that import intensively from lower-income countries, neither and both. 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 9 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

[17]In Figure 2 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.

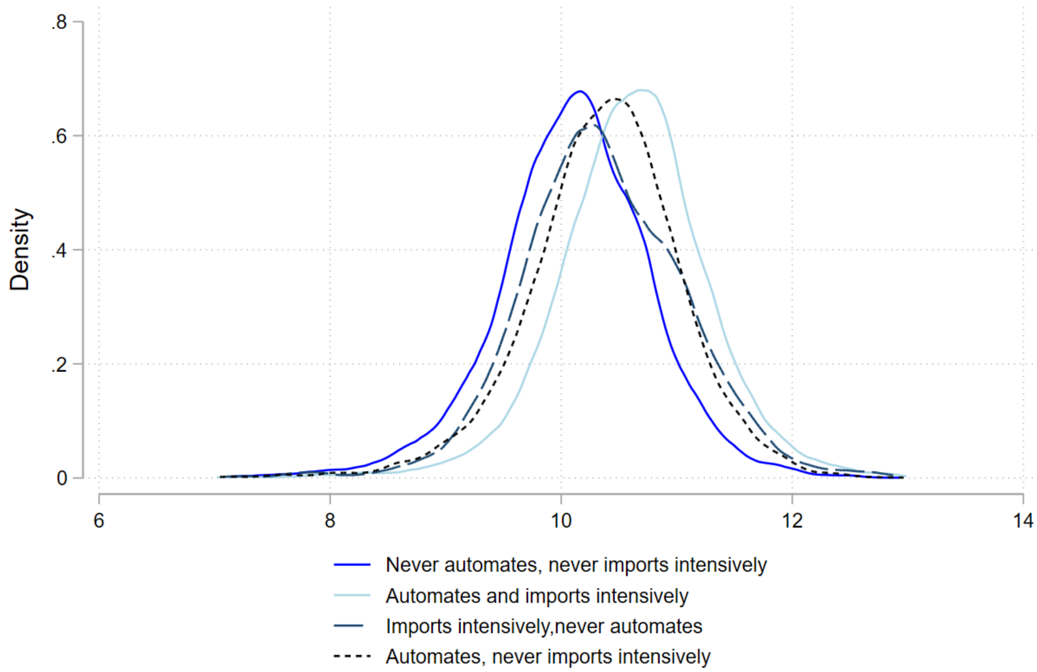


Figure 3: Labour productivity distribution by automation and importing from lower-income countries

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.

that only automate.

Figure 10 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.

4. Automation and offshoring with heterogeneous firms

In Section 3 we demonstrated that even within narrowly defined industries and regions, firms that select into automation are already more productive than firms that do not and that this productivity gap in then wider in any given time period between firms that have already automated and those that have not. Other recent studies, such as Acemoglu et al. (2020) and Aghion et al. (2020) have also started to document the impact of automation on the reallocation of economic activity between firms. To explain these empirical patterns we require a modelling framework that incorporates firm heterogeneity. Our first building block is therefore to incorporate Melitz (2003) style firm heterogeneity and fixed costs into a simplified version of the canonical task-based automation framework in Acemoglu and Restrepo (2018c). To explain why only a subset of the most productive firms select into automation, we incorporate upfront fixed costs of automation, taking inspiration from Bustos (2011), who models technology adoption as involving an upfront fixed cost and a marginal cost reduction.

Existing task-based models of automation have also typically not allowed for the additional dimensions of international trade or multinational activity. We demonstrated in Section 3 that firms that automate are also on average far more likely to engage in international trade, trade greater volumes conditional on doing so, and are more likely to have foreign affiliates, suggesting that international orientation may be important for understanding the causes and effects of automation. We therefore also incorporate the option to offshore tasks into our model, building upon a variant of Acemoglu and Autor (2011) where firms can either automate tasks, offshore them or produce them at home.[18] We also found in Section 3 that in Spain only a subset of the most productive manufacturing firms import from, or have affiliates in, lower income countries.[19] We hence follow a variant of one of the models discussed in Antràs and Yeaple (2014) in also modelling offshoring as involving an upfront fixed cost and a marginal cost reduction.

4.1 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 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 a simplified version of Acemoglu and Restrepo (2018c) we assume that production is characterised by combining a unit measure of tasks according to a constant elasticity of substitution aggregator. To simplify our analysis, however, we do not allow for the introduction of new tasks. The production of variety ω involves performing tasks $x \in [0, 1]$. The output of firm ω is then:

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

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 (2018c) 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 $m(x)$.[20] Following Acemoglu and Restrepo (2018c), we assume that labour in the home country, labour in the offshore country and machines are perfectly

[18]For simplicity we conceptualise our model here in terms of offshoring generally, rather than importing or vertical FDI specifically. This model could be expanded to include both separately, with higher fixed costs for vertical FDI as in Antràs and Yeaple (2014), or it could be further be expanded to additionally also allow for horizontal FDI.

[19]This sorting pattern is consistent with the evidence on selection into importing in Bernard et al. (2009) who show that not only U.S. exporting firms but also U.S. importing firms appear to be more productive than purely domestic producers

[20]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).

substitutable factors of production. Tasks are ordered by the productivity of home labour in completing them, $\gamma_{LH}(x)$. We first present the model allowing only for the offshoring of tasks and then subsequently incorporate the role of automation.

4.2 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 has the greatest comparative advantage in performing. For example, these could be activities that would typically be conducted at the firm headquarters in a high-income country, such as managerial activities. The tasks that are possible to offshore can be performed by labour at home or offshore labour, but performing a task with offshore labour involves an iceberg transport cost $\tau > 1$ 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:

$$q(\omega, x) = \begin{cases} \mathbb{1}[H=1]\gamma_{LH}(x)l_H(\omega, x) + \mathbb{1}[O=1]\frac{\gamma_{LO}(x)l_O(\omega,x)}{\tau} & \text{if } x \in [0, I^O] \\ \\ \gamma_{LH}(x)l_H(\omega, x) & \text{if } x \in [I^O, 1] \end{cases} \tag{4}$$

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 (2018c), 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 $\Gamma_F^{(a,b)} = \left(\int_a^b \gamma_F(x)^{\sigma-1}dx\right)^{\frac{1}{\sigma}}$, 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 they choose to offshore $q^O(w)$ or if they do not offshore $q(w)$ as:

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

and

$$q(\omega) = \varphi(\omega)\left[\Gamma_{LH}^{(0,1)} L_H^{(0,1)}(\omega)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \tag{6}$$

4.3 Preferences and profit maximisation

Preferences across varieties have the standard CES form as in Melitz (2003), with an elasticity of substitution $\kappa = 1/(1-\theta) > 1$. These preferences lead to demand function $q(\omega) = EP^{\kappa-1}[p(\omega)]^{-\kappa}$ for every variety ω , where $p(\omega)$ is the price of each variety, $P = [\int_0^M p(\omega)^{1-\kappa} d\omega]^{\frac{1}{1-\kappa}}$ 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. We assume that labour abroad and at home are fixed and inelastically supplied.

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:

$$MC^O(\omega) = \frac{1}{\varphi(\omega)}\left(\Gamma_{LO}^{(0,I^O)} w_O^{1-\sigma} + \Gamma_{LH}^{(I^O,1)} w_H^{1-\sigma}\right)^{\frac{1}{1-\sigma}} \tag{7}$$

$$MC(\omega) = \frac{1}{\varphi(\omega)}\left(\Gamma_H^{(0,1)} w_H^{1-\sigma}\right)^{\frac{1}{1-\sigma}} \tag{8}$$

Taking the second part of the right hand side of 8, $\left(\Gamma_H^{(0,1)} w_H^{1-\sigma}\right)^{\frac{1}{1-\sigma}}$ as the numeraire and equating this to 1, we can then write the marginal cost functions as:

$$MC^O(\omega) = \frac{\alpha}{\varphi(\omega)} \qquad \text{and} \qquad MC(\omega) = \frac{1}{\varphi(\omega)} \tag{9}$$

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

4.3.1 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:

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

$$\pi(\varphi(\omega)) = (1-\theta)EP^{\frac{\theta}{1-\theta}}\left[\frac{1}{\theta}MC\right]^{\frac{-\theta}{1-\theta}} - F_e \tag{11}$$

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 $\Omega(\varphi(\omega)) = (1-\theta)EP^{\frac{\theta}{1-\theta}}\left[\frac{1}{\theta}\frac{1}{\varphi(\omega)}\right]^{\frac{-\theta}{1-\theta}}$ we have that firms will offshore when:

$$\pi^O(\varphi(\omega)) - \pi(\varphi(\omega)) > 0 \Leftrightarrow \Omega(\varphi(\omega))(\alpha^{\frac{-\theta}{1-\theta}} - 1) > F_O \tag{12}$$

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

$$\Omega(\varphi^*(\alpha^{\frac{-\theta}{1-\theta}} - 1) = F_O \tag{13}$$

4.4 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. 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:

$$q(\omega, x) = \begin{cases} \mathbb{1}[H=1]\gamma_{LH}(x)l_H(\omega,x) + \mathbb{1}[O=1]\frac{\gamma_{LO}(x)l_O(\omega,x)}{\tau} + \mathbb{1}[M=1]\gamma_M(x)m(\omega,x) & \text{if } x \in [0, I^M] \\ \mathbb{1}[H=1]\gamma_{LH}(x)l_H(\omega,x) + \mathbb{1}[O=1]\frac{\gamma_{LO}(x)l_O(\omega,x)}{\tau} & \text{if } x \in [I^M, I^O] \\ \gamma_{LH}(x)l_H(\omega,x) & \text{if } x \in [I^O, 1] \end{cases} \tag{14}$$

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 perfectly substitutable factors of production. 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:

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

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

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.

4.4.1 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:

$$MC^{OM}(\omega) = \frac{1}{\varphi(\omega)}\left(\Gamma_{M}^{(0,I^{M})} r^{1-\sigma} + \Gamma_{LO}^{(I^{M},I^{O})} w_{O}^{1-\sigma} + \Gamma_{LH}^{(I^{O},1)} w_{H}^{1-\sigma}\right)^{\frac{1}{1-\sigma}} \tag{17}$$

$$MC^{M}(\omega) = \frac{1}{\varphi(\omega)}\left(\Gamma_{M}^{(0,I^{M})} r^{1-\sigma} + \Gamma_{LH}^{(I^{M},1)} w_{H}^{1-\sigma}\right)^{\frac{1}{1-\sigma}} \tag{18}$$

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

$$MC^{OM}(\omega) = \frac{\beta}{\varphi(\omega)} \qquad \text{and} \qquad MC^{M}(\omega) = \frac{\delta}{\varphi(\omega)} \tag{19}$$

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:

$$\pi^{M}(\varphi(\omega)) = (1-\theta)EP^{\frac{\theta}{1-\theta}}\left[\frac{1}{\theta}MC^{M}\right]^{\frac{-\theta}{1-\theta}} - F_M - F_e \tag{20}$$

$$\pi^{OM}(\varphi(\omega)) = (1-\theta)EP^{\frac{\theta}{1-\theta}}\left[\frac{1}{\theta}MC^{OM}\right]^{\frac{-\theta}{1-\theta}} - F_M - F_O - F_e \tag{21}$$

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 ($\kappa > 1$), but firms must pay the higher fixed cost. The benefits of automating or offshoring are also increasing in firm productivity.

4.5 Advances in automation technologies

This model allows for three types of technological progress in automation. First, at the extensive margin of automation, an increase in I^M. Second, at the intensive margin of automation, an increase in $\gamma_M(x)$ or a decrease in r. Third, a decline in the fixed cost of automation through 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. In our empirical analysis we will measure this expansion of the extensive margin using robotics patents.

Holding I_O fixed, an increase in I_M will cause firms that are already automating to conduct a greater share of tasks using machines. A subset of marginal firms will also be induced to start automating because of the further marginal cost reduction generated by being able to use machines for a wider range of tasks. In our empirical analysis we will focus on the impact of robot adoption. We therefore look at the implications for the second category of firms that are induced to start automating using robots as a consequence of the expansion of I_M.

4.5.1 Within-firm implications of robot adoption

The model generates the following predictions about the impact of robot adoption:

- **For firms that have already offshored:**
  1. Robot adoption will reduce their share of tasks conducted by offshore labour.
  2. Robot adoption will reduce their production costs, meaning that they can charge lower prices, increase revenues and expand, increasing demand for offshore labour in tasks that can't be automated and home labour in tasks that can't be automated or offshored. Robot adoption thus has two similar effects on offshore labour as in Acemoglu and Restrepo (2018c): the negative displacement effect whereby tasks are replaced by machines and the positive productivity effect through reduced production costs.

3. For home labour, however, there is no displacement effect but only a productivity effect because only offshore tasks are displaced by robots.

- **For firms that have not already offshored:**

1. Robot adoption will reduce their share of tasks conducted by home labour.
2. They will also experience a positive productivity effect through lower production costs.
3. The higher revenues could make it profitable to now pay the fixed cost of offshoring and start offshoring the subset of tasks that cannot be automated but can be offshored. This would generate a further displacement and productivity effect for home labour.
4. For offshore labour, robot adoption could therefore generate a positive productivity effect.

4.5.2 Between-firm implications of automation

One of the key implications of incorporating Melitz (2003) style firm heterogeneity and fixed costs is that automation also induces between-firm reallocation of economic activity. 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 firm survival cutoff, meaning that the least productive firms that cannot automate are forced to exit and surviving non-automating firms reduce their revenues and demand for factors of production. When I_M increases, the expected productivity level of surviving firms is therefore higher and the per period expected profits of surviving firms are also higher.

4.6 Extensions

In this framework we have made a number of simplifying assumptions that have not allowed for some of the other forces that could counteract the displacement effects of automation as discussed in Acemoglu and Restrepo (2018a). Allowing automation to lead to capital accumulation or to generate new tasks could both result in further countervailing impacts on the demand for offshore labour or labour at home.

5. Empirical strategy

In this section we now attempt to evaluate the causal impact of automation on our key firm outcomes, focusing from this point onwards on robot adoption only. The baseline specification we aim to estimate is:

$$\mathrm{X}_{it} = \alpha + \beta \mathrm{Robots}_{it} + \theta \text{industry-year}_{it} + \phi \text{region-year}_{it} + \gamma_i + \epsilon_{it} \tag{22}$$

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, $\text{industry-year}_{it}$ and region-year_{it} are firm, industry-year and region-year fixed effects.[21] 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 22. First, this equation could suffer from reverse causality. In Section 3 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, redirecting activities at their headquarter firms towards more innovative and technology-focused production. Alternatively, it is plausible that firms that have just offshored production could be less likely to adopt technology due to having less incentive to reduce labour costs. This reverse causality could result in the demeaned robot use dummy variables being correlated with the demeaned error term, resulting in biased

[21] 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.

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 adoption 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 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.[22] We then develop an industry-region level measure of 'exposure' using the 1980s occupational composition of employment in a given region and industry and the patent measures for each occupation code. The instrument for robot use by firm i in industry j and region r at time t is then:

$$\text{robot}_{irjt} = \text{exposure}_{rjt}^{robotpatent} \tag{23}$$

[22]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.

where

$$\text{exposure}_{rjt}^{robotpatent} = \sum_{o=1}^{n} \text{automatable}_{ot}^{patent} \times \text{employment}_{orj1981} \tag{24}$$

where $\text{automatable}_{ot}^{patent}$ 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 22 in levels with firm fixed effects. Because our instrument is at the industry-region-year level, there is insufficient variation across industries within different regions to include both industry-year and region-year fixed effects and so we aggregate the NACECLIO industries to a higher level industry grouping and include industry group-year fixed effects, along with region-year fixed effects.[23]

5.2.1 Insights from exposure measures

Most and least exposed occupations: Table 15 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 4 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

[23]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.

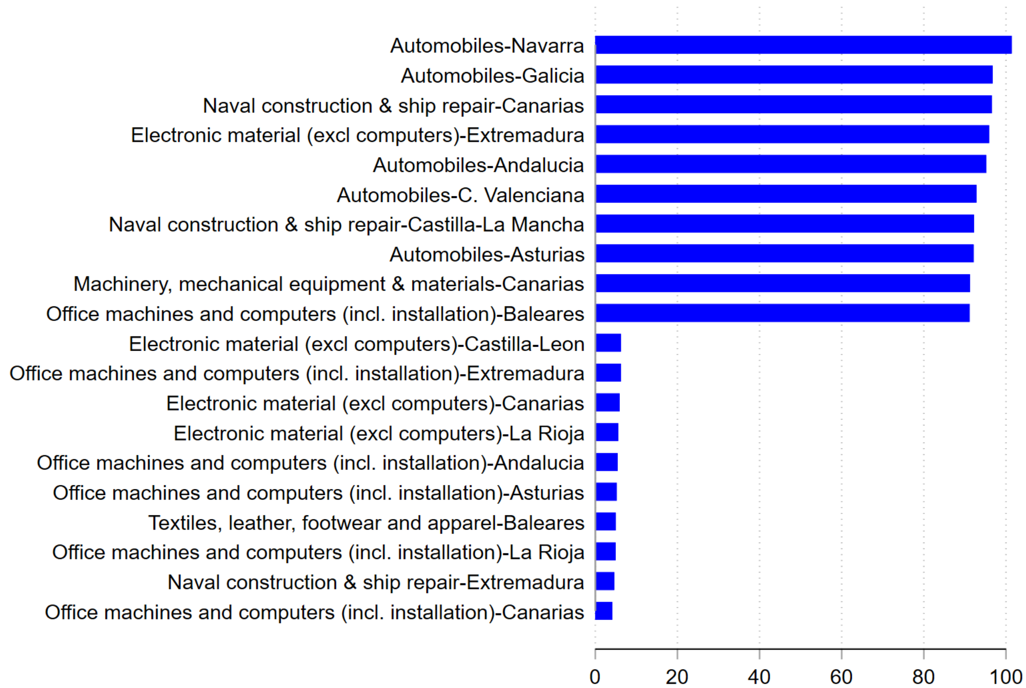


Figure 4: Top 10 industry-region pairs with highest and lowest median exposure

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

the same industries in different regions, suggesting that the same industry can have a different occupational composition depending on its location. For example in the 'Electronic Material (excl Computers)' industry in Castilla-Leon the most prevalent occupation is 'Electrical Fitters and Related Electrical and Electronics Workers' at 39% of employment, with a very low robot exposure score, while the same occupation only accounts for 19% of employment in the same industry in Extremadura with the other highly robot exposed occupations like Machinery Fitters, Machine Assemblers and Precision Instrument Makers making up a high share of employment.

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 'arc welding'. In a similar vain to Graetz and Michaels (2018) we hand match robot applications to ISCO 68 occupation codes.[24] 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 and the time-varying occupation scores are 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. [25] 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 more concerning possibility could be that robotics inventions have targeted the same occupations that Spanish firms have wanted to offshore. This could be the case if these are particularly labour intensive occupations 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 adoption

[24]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.

[25]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.

on offshoring. Anecdotally, it does not appear that this is the case; robots are still incapable of many labour intensive tasks that are typically offshored. Additionally we found that a similar patterns holds in Spain as that described in Acemoglu and Restrepo (2019) that robot adoption is typically concentrated in different industries to those that have experienced a high degree of offshoring.

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.[26]

6. Results

6.1 Baseline results

Table 5 presents the baseline fixed effects results without instrumenting for robot use. These results show that without using an IV, starting to use robots is associated with an increase in the value of imports from lower-income countries and the intensity of imports from lower-income countries, a lower share of imports from lower-income countries, higher employment, greater production of goods or services, higher labour productivity and higher TFP.

Table 6 next 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

[26]A final concern cold be around the impact of import competition. We have not explicitly included the role of import competition in our analysis. 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.

TABLE 5. BASELINE 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	0.41***	0.0019***	-0.0090*	-0.0051	-0.00089
	(0.088)	(0.00072)	(0.0054)	(0.0064)	(0.0030)
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	0.054***	0.097***	-0.0062**	0.032***	0.052***
	(0.0061)	(0.0076)	(0.0031)	(0.0087)	(0.0095)
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 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.

data and our instruments being at this level.[27] 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 positive statistically significant impact on imports from lower-income countries. a weakly significant 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 adoption 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

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

TABLE 6. 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.

infinite. In addition, our robot adoption variable takes only the values 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. 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 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 adoption on domestic outcomes is also substantial. Table 19 in Appendix B also includes this and all other results relating to TFP for Olley-Pakes TFP instead, showing little effect of these different ways of calculating 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, suggesting that OLS results are biased downwards. This is in line with findings in Aghion et al. (2020) and Artuc et al. (2018) who both find IV results to be higher than OLS. Second, for OLS there is no statistically significant relationship between robots and the number of lower-income country affiliates. One explanation for these differences could be that firms that have already started offshoring to lower-income countries are subsequently less likely to adopt robots and so OLS coefficients are biased towards zero. It is also plausible that firms that have just opened affiliates abroad, particularly if for labour cost saving reasons, may be less interested in adopting robots at home.

We also repeat these baseline results with weightings by baseline firm output. Table 17 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 16 in Appendix B.

6.2 Extensive margin and changes to employment and activities at affiliates

We next explore how robot adoption affects the extensive margin of importing from, or opening affiliates in, lower-income countries. Our results above in Table 6 demonstrated that there was a very high coefficient for the impact of robot adoption 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 7 first displays results for the impact of robot adoption 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 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

TABLE 7. 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.

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. In terms of the primary activity conducted at the main affiliate, we find a positive impact of robot adoption 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 may be 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.

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

TABLE 8. SEQUENCING OF IMPORTING INTENSIVELY AND ROBOT ADOPTION

	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 adoption 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.

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 8 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 3, we define importing intensively from lower-income countries as being in the top 20% of the sample in terms of import intensity from lower-income countries, equivalent to importing 1% or more of total output.[28]

Panel (a) displays the results for the limited 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 adoption. 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 the model prediction that the sequencing of these decisions matters for their impact. In Figure 18 we also show that these results hold if we instead define importing intensively as being in the top 20% within industries, 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.

[28]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.

TABLE 9. 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.

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 6 showed a strong positive impact of robot adoption 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 adoption affected total labour costs. Column 1 in Table 9 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'. Column 2 shows that starting to use robots does indeed have an impact on the changing of regular workers, with robot adoption leading firms to be around 44% more likely to report a change. Columns 3-6 explore the impact on different types of employment.

TABLE 10. 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.

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 adoption 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. Our dataset does not include the total number of robots used, but does provide one variable of relevance for also studying the intensive margin of automation: 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 10 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 adopters 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.

7. Robustness

7.1 Offshoring instrument control

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 in the baseline specification, we include both industry group-year and region-year fixed effects. Here we provide an additional robustness check where we also control for a firm level variable as outlined in Section 2.5 that is 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 adoption is not in some way reflecting these global supply shocks, as opposed to only the technology supply side of robotics inventions.

TABLE 11. 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.

Table 11 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 for external factors that made firms more likely to offshore has not biased our results for the

TABLE 12. 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.

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, following the method of Chen and Steinwender (2019), outlined in the Data section. Import tariffs for Spain are set at the EU level and are hence plausibly exogenous to Spanish

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** (2.23)	0.048** (0.020)	0.15 (0.17)	0.42* (0.23)	0.028 (0.10)
First stage coef.	0.021*** (0.0030)	0.021*** (0.0030)	0.021*** (0.0030)	0.021*** (0.0030)	0.021*** (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 (0.21)	1.58*** (0.33)	-0.067 (0.22)	1.18*** (0.28)	1.73*** (0.36)
First stage coef.	0.021*** (0.0030)	0.021*** (0.0030)	0.021*** (0.0030)	0.021*** (0.0030)	0.021*** (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.

firms. We construct two control variables: one for MFN import tariffs on the intermediate inputs of an industry, which we denote as 'imported input tariffs', and the other for MFN import tariffs on products in the same industry, which we denote as 'same-industry import tariffs'.

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

7.3 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 adoption. The results are qualitatively similar, with the main difference being that the coefficients on domestic employment and the labour share are now not statistically significant, suggesting that these results are less robust than for the other outcome variables. The coefficient for the value of imports from 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.

7.4 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 20 in Appendix B repeats the analysis in Table 6 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.

7.5 Is this just the automotive sector?

The industry in our dataset with the highest prevalence of robot adoption 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 industry, that is particularly reliant on robots for production. We hence also try removing this sector from our analysis. Table 21 in Appendix B displays the results. We find that when we exclude this sector, the impact of robot adoption on lower-income 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.

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 22 in Appendix B 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.

7.7 Lagged multinational status and TFP controls

There are a few other possibilities that could explain these results. One possibility is that these results reflect the fact that firms that become multinationals start both adopting robots and importing from lower-income countries, or opening affiliates there, at the same time. In Table 23 in Appendix B we explore whether this is the case by adding a control variable for the four year lag of the firm's multinational status. This variable is unlikely to be exogenous but here we merely assess whether its inclusion alters our key results. This control has a statistically significant and positive effect on all international outcome variables except for the affiliate share and on employment and output, with a negative effect on the labour share. However, including it does not dampen the significance of the coefficients for robot use and only serves to increase their magnitude.

An additional possibility is that there remain firm-specific time varying shocks that we are not successfully managing to rule out with our IV strategy or controls and other robustness checks. We therefore also directly explore the impact of including lagged TFP controls. Table 24 displays that the coefficient for the impact of robot use on imports from lower-income countries is now slightly less significant and lower in magnitude, but still significant to the 5% level, while the coefficients for import intensity and affiliates remain at the same significance level with larger magnitudes. The robot coefficient in the employment regression is now insignificant, while for the other domestic outcomes the coefficients remain at the same significance level but a slightly lower order of magnitude. These results generally suggest that the key results remain robust to explicitly controlling for lagged firm-level TFP shocks.

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 adoption 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 adoption 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 adoption 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 about the consequences of automation for reshoring have over-simplified what is, in fact, a complex relationship and firm level data is important for understanding this relationship in detail. 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 lower-income countries. 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, through the channel of firms that imported intensively before automating reducing their import share from lower-income countries, 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.

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Online Appendix

A. Additional figures

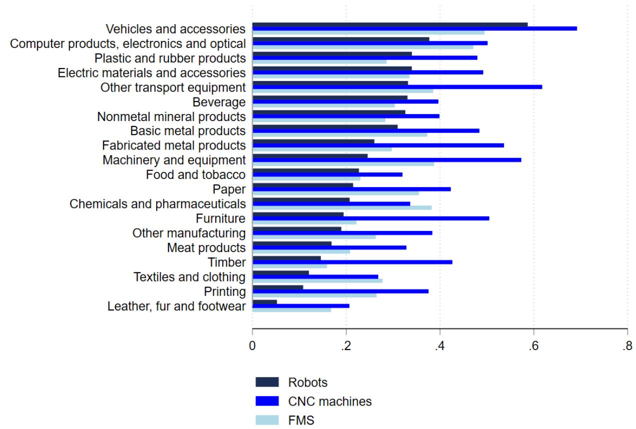


Figure 5: Share of firms using each technology, by industry

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

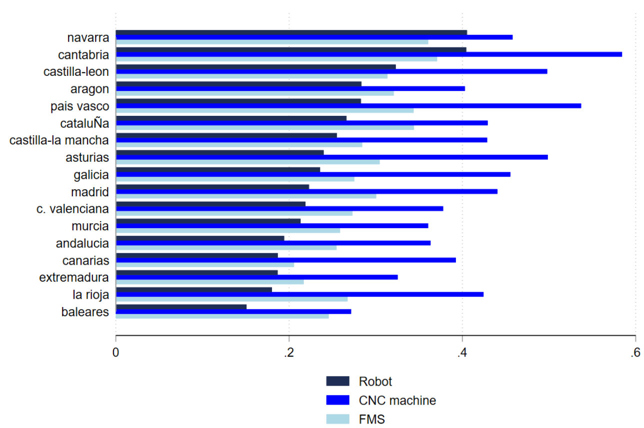
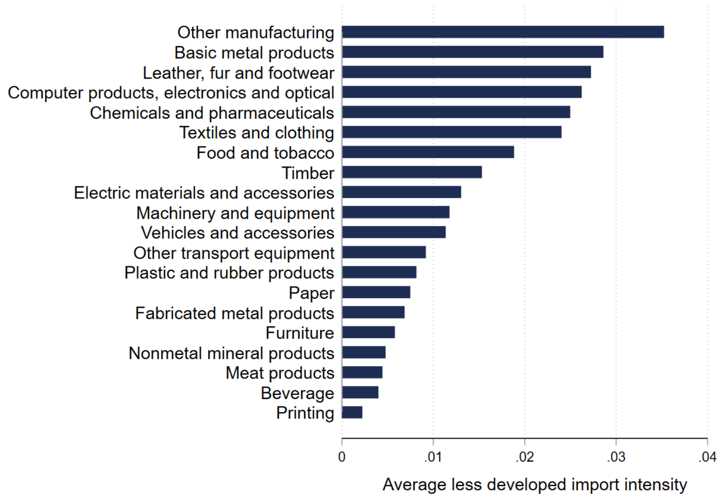
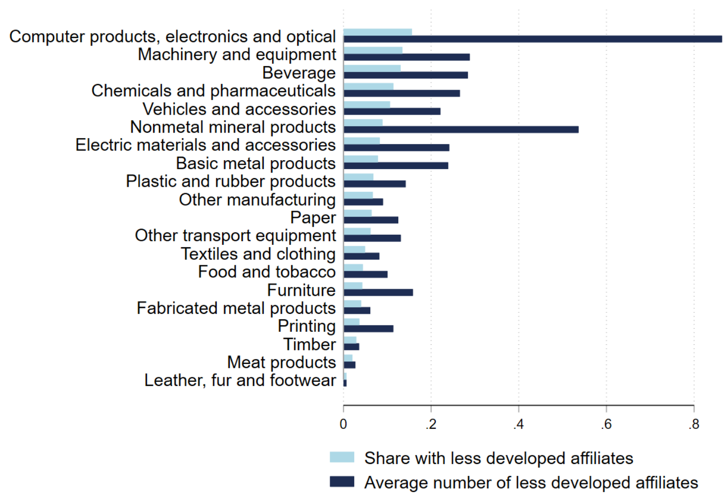


Figure 6: Technology use by region

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



(a) Import intensity



(b) Affiliates

Figure 7: 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.

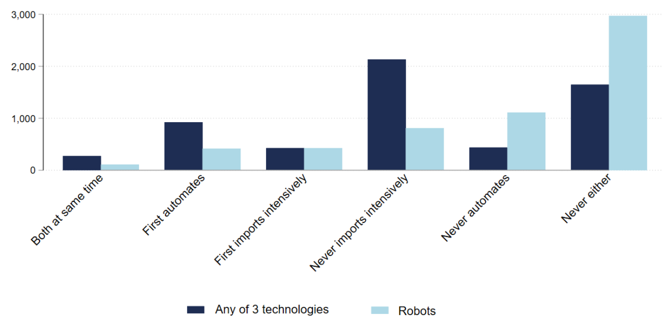


Figure 8: Sequencing of automation and importing intensively from lower-income countries

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.

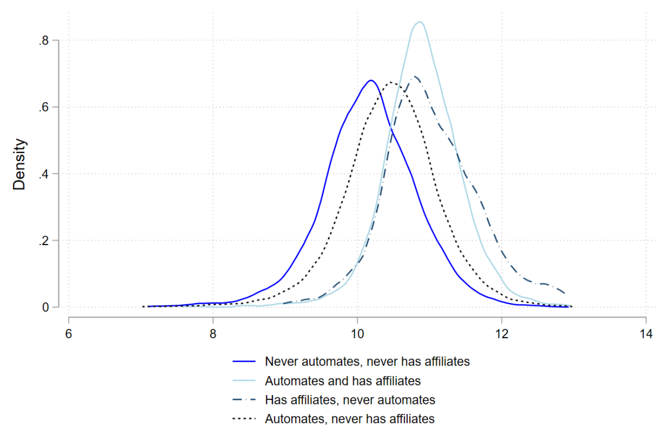
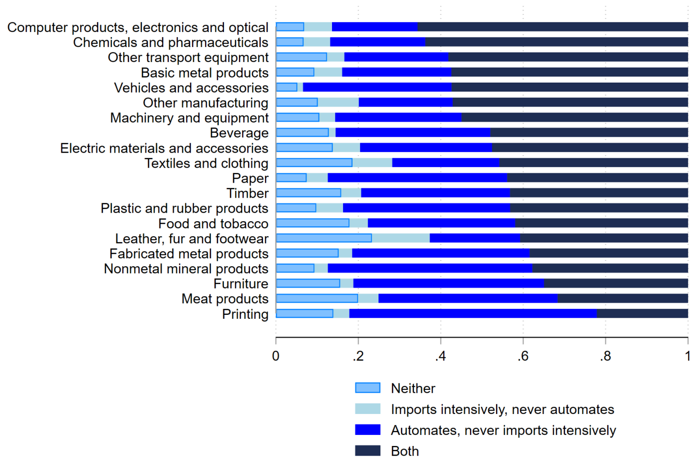
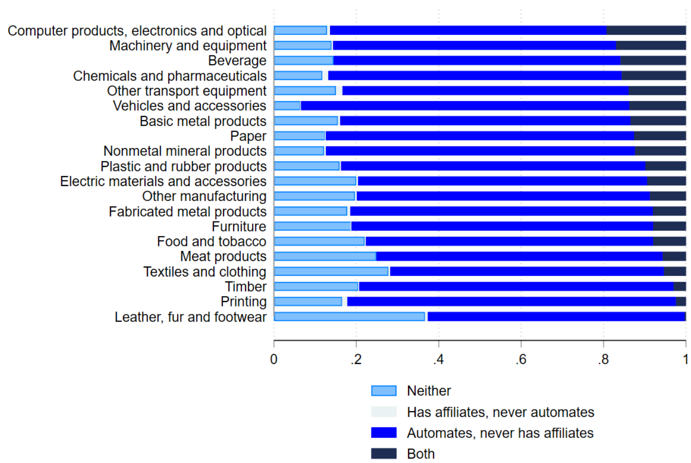


Figure 9: Labour productivity distribution by automation and less dev MNC status

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 10: 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 14. 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 15. 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 16. 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 17. 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 18. 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 lower-income 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 19. 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.

TABLE 20. 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.

TABLE 21. 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** (3.47)	0.062* (0.033)	-0.095 (0.22)	0.59* (0.31)	0.062 (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*** (0.37)	4.22*** (0.85)	-0.70*** (0.18)	1.90*** (0.49)	4.20*** (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.

TABLE 22. 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***	11.9***	11.6**	0.62
	(3.09)	(2.95)	(4.86)	(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.

TABLE 23. CONTROLLING FOR LAGGED MNC STATUS

	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	13.9***	0.065**	-0.0093	0.80*	0.13
	(3.78)	(0.031)	(0.18)	(0.42)	(0.16)
Lagged MNC status	1.21***	0.0074***	0.043***	0.038*	0.0018
	(0.28)	(0.0021)	(0.0092)	(0.022)	(0.0090)
First stage coef.	0.0054***	0.0054***	0.0052***	0.0034***	0.0034***
	(0.00096)	(0.00096)	(0.00096)	(0.0011)	(0.0011)
First stage F stat	31.6	31.9	29.4	9.22	9.22
Observations	26357	26340	26476	19238	19216
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	0.65**	2.41***	-0.52***	1.26***	3.28***
	(0.30)	(0.51)	(0.12)	(0.33)	(0.66)
Lagged MNC status	0.088***	0.15***	-0.023***	0.0015	0.057
	(0.015)	(0.034)	(0.0074)	(0.022)	(0.048)
First stage coef.	0.0052***	0.0052***	0.0052***	0.0051***	0.0052***
	(0.00096)	(0.00096)	(0.00096)	(0.00096)	(0.00098)
First stage F stat	29.4	29.0	29.1	28.3	27.5
Observations	26445	26409	26408	26225	25715
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 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.

TABLE 24. CONTROLLING FOR LAGGED TFP

	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	9.68**	0.076*	0.013	0.74*	0.11
	(4.12)	(0.039)	(0.23)	(0.44)	(0.17)
Lagged log TFP	0.090	0.00045	-0.0057	0.016*	0.00061
	(0.10)	(0.00095)	(0.0057)	(0.0091)	(0.0029)
Patent IV first stage coef.	0.0047***	0.0047***	0.0044***	0.0032***	0.0032***
	(0.0010)	(0.0010)	(0.0010)	(0.0011)	(0.0011)
Lagged log TFP first stage coef.	0.011**	0.011**	0.011**	0.010*	0.010*
	(0.0053)	(0.0053)	(0.0053)	(0.0060)	(0.0060)
First stage F stat	31.6	31.9	29.4	9.22	9.22
Observations	26357	26340	26476	19238	19216
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	0.38	2.09***	-0.47***	1.13***	2.86***
	(0.36)	(0.60)	(0.13)	(0.40)	(0.76)
Lagged log TFP	0.11***	0.12***	-0.00089	0.0077	0.15***
	(0.0091)	(0.016)	(0.0035)	(0.013)	(0.023)
Patent IV first stage coef.	0.0044***	0.0044***	0.0044***	0.0044***	0.0042***
	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)
Lagged log TFP first stage coef.	0.011**	0.012**	0.012**	0.011**	0.014**
	(0.0053)	(0.0053)	(0.0053)	(0.0053)	(0.0057)
First stage F stat	19.1	19.0	19.0	18.7	16.6
Observations	22161	22139	22138	22025	21820
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 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.

C. Additional definitions and data

Spain's largest non-EU and non-OECD import partners

In terms of total import value cumulatively between 1990 and 2016, Spain's largest import partners in the lower-income group of non-OECD and non-EU countries 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 with 0.8%, India with 0.8% and Indonesia with 0.6%, based on UNCOMTRADE import data.

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 25 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 25. 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. .

Construction of offshoring instrument control variable

We take this export data by ISIC Rev 3 industry from UNCOMTRADE, accessed via the WITS platform from the World Bank.[29] We use an ISIC Rev 3-NACE Rev 1 Crosswalk provided by Eurostat to map these to NACE Rev 1 industries.[30] 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 industries according to the baseline purchase share specified in Spain's I-O table for imports obtained from the Instituto Nacional D'Estistica (INE). [31] Then for firm i in industry j at time t, the instrument for offshoring O_{ijt} is defined as:

$$O_{ijt} = \sum_{c} s_{ijc,base} \times \text{IO share}_{jk,base} \times EX_{ckt} \tag{25}$$

where $s_{ijc,base}$ is firm i in industry j's share of imports from region group c in their first reporting period, 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.

[29]wits.worldbank.org

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

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

Construction of import tariff controls

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.