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“International trade: Effects of computerization and offshoring in developing countries”

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International trade: Effects of computerization and offshoring in developing countries

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Abstract

The adoption of new technologies has consequences for the evolution of global value chains and international trade. Antràs (2020) argues that whereas in the 1990's it was profitable to fragment production processes, now computerization reduces labor costs and substitutes the offshoring of certain activities. Using data on imports from six developed countries (sourced from 40 developing countries) between 2000 and 2016 we provide evidence on the effects of computerization and offshoring in trade patterns. The results show that imports of developed economies in sectors in the 90th percentile of the share of employment at risk of computerization relative to an industry in the 10th percentile fell (depending on the specification) between 19 to 25 percentage points more for sectors with higher ICT adoption during this period, effect that increased using an IV strategy. Furthermore, we find that an initial higher offshoring has a negative effect on imports (26 and 44 percentage points without and with IV) in countries with greater technology capital. Current labor-replacing technologies, that are mainly in occupation with low wages, are changing the comparative advantages of developing economies, which should invest in reallocation policies to cope with this new reality.

Keywords: Computerization, ICT, offshoring, robots, trade, global value chains (GVC)
JEL: F1, F6, O3

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Acronyms

ALM: Autor, Levine and Murnane

FO: Frey and Osborne

GVC: Global Value Chains

HS: Harmonized System

ICT: Information and Communication Technology

IFR: International Federation of Robots

ISIC: International Standard Industrial Classification

NAICS: North American Industry Classification System

OaRA: Occupations at Risk of Automation

OECD: The Organisation for Economic Cooperation and Development

PPML: Pseudo Poisson Maximum Likelihood

WIOD: World Input Output Database

1 Introduction

In the late 1980s, the fragmentation of production processes across the world (also known as offshoring) increased significantly. This, because the information and communication technology (ICT) revolution has enabled the growth of global value chains (GVC). At the same time, the fall in the barriers and cost of trade, as well as the increase in labor supply (because of political changes and the adoption of market economy systems), reinforce a process of globalization that today could be changing (Antràs, 2020).

Higher capacities of transmission and process of information by computers, along with the expansion in internet use, allowed firms to cut costs by moving production processes to developing countries[1]. However, the advances in these technologies and the growing adoption of new ones such as artificial intelligence, 3D printing, or industrial robots is becoming an alternative to offshoring. The decision between computerization/automation[2] and offshoring depends on costs, labor supply conditions, access to credit, regulations in labor markets, among others (Stapleton, 2019). Thus, financial capital and higher labor costs have put developed countries at the frontier of adoption of these new technologies to substitute task initially performed by workers in low-wage occupations. We attempt to address how this has changed trade between developed and developing countries, focusing on the consequences on the latter due to the potential lost in it's comparative advantage.

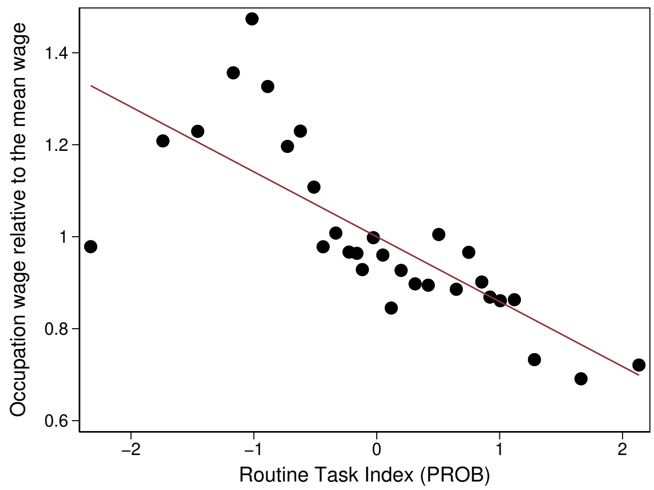
New technologies reduce the demand for tasks previously performed by humans, increasing efficiency and reducing production costs. Autor et al. (2003) -from now on ALM- argue that technological progress substitutes labor in performing routine tasks. Frey and Osborne (2017)- from now on FO- extend this idea and claim that technological progress can replace routine and any non-routine task that is not subject to any engineering bottlenecks with respect to computerization[3]. Figure 1 shows that occupation characterized by more routine tasks (Occupations at Risk of Automation, OaRA) in the United States, and therefore subject to computerization, are also the ones with lower wages. Thus, new technologies are changing countries comparative advantages in a way that developing countries are losing theirs in low-wage sectors (Antràs, 2020 ; Carbonero et al., 2020). By a Heckscher-Ohlin argument, the abundant factors of production in low-income countries (e.g., low skilled workers) are hurt by these new technologies (Pedemonte et al., 2019).

[1]Before the development of ICT, the share of inputs sourced from abroad was minimal. The exchange of intermediate goods and services was primarily between developed countries (G7). This change around the 1990s when the "New Globalization" or second GVC revolution started. Developed economies reallocate some stages of the production process in developing countries to reduce labor costs (Baldwin, 2018).

[2]Throughout the document, we will use the terms "computarization" and "automation" interchangeably.

[3]The authors define computerization as "job automation by means of computer-controlled equipment". They established that occupations that involve complex perception and manipulation tasks, creative intelligence tasks and social intelligence tasks are the ones that wouldn't be replace by computer capital (these are the engineering bottlenecks).

Figure 1: Wages and risk of computerization



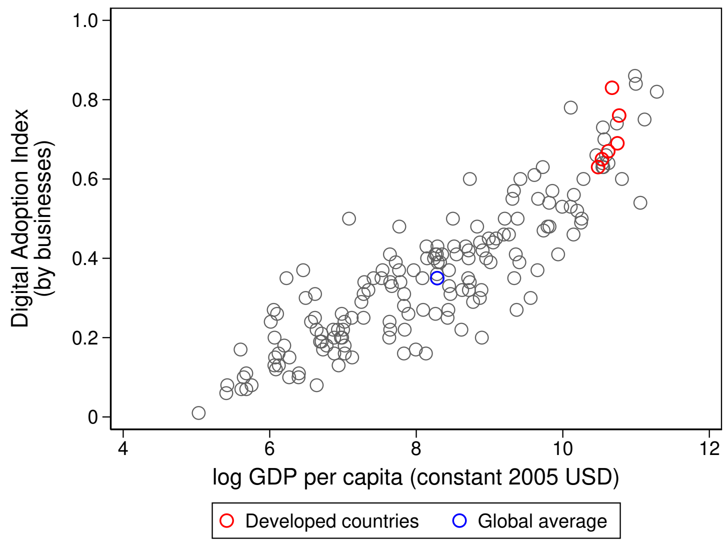
Note: Routine Task Index from Autor et al. (2003) proxies the probability of computerization at occupational level. Measure standardized (with mean 0 and standard deviation 1). Data on wages for the United States in the year 2000.

However, the effects for developing countries could be positive if we consider that the improvement of automation technologies is associated with capital accumulation and higher productivity in developed countries (Acemoglu and Restrepo, 2019). A higher level of efficiency and stock of capital in developed countries could boost the demand for intermediate inputs from developing countries due to an scale effect (Antràs 2020 ; Artuc et al., 2019).

The impact of any of the previous effects on welfare of developing economies, comparative advantage and/or scale, is linked to the strong integration of global markets, as well as the participation in different stages of global value chain (GVC). Previous studies show that the development of GVC was accompanied with a significant reduction of poverty in developing countries. Coupled with this, offshoring provided better labor opportunities and an increased in productivity (Stapleton, 2019). For this reason, it's important to evaluate empirically how technological advances reshape developing countries participation in global trade in general, and in GVC in particular.

Despite its relevance, evidence on the impact of this new wave technologies/computerization in the last decades on trade is scant. Empirical progress on this topic has focused on the effects of these new technologies on employment and wages in developed countries. They are the ones that have incorporated new technologies more heavily for the advantages in wages that it entails. Higher financing costs, low wages and lack of human capital reduce firms' incentive to invest in these technologies in developing countries. Figure 2 shows, in fact, that the six developed countries in our sample have a higher Digital Adoption Index in comparison with the group of developing countries (and the average for the world).

Figure 2: Digital Adoption Index (DAI) by businesses



Source: World Bank Group (2016). Note: Figure 2 presents the DAI for 166 countries in the world, the 6 developed countries in our sample (in red: France, Denmark, US, United Kingdom, Japan and the Netherlands) and the global average (in blue). This DAI is the simple average of four normalized indicators: the percentage of businesses with websites, the number of secure servers, the speed of download, and 3G (third-generation) coverage in the country.

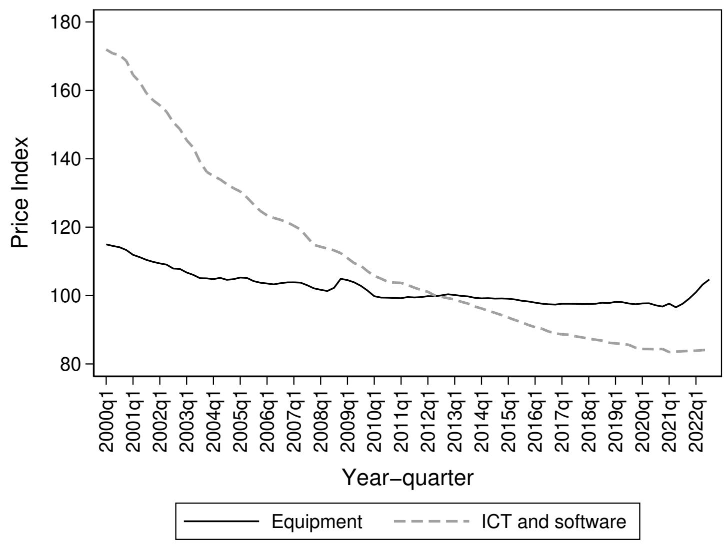
Empirical progress on the trade channel has been hindered by lack of information on dis-aggregate sector investment in these new technologies. Section 2 presents previous results, which are ambiguous, and they do not study the interaction effect of computerization and offshoring on imports from developing markets. In this paper, we overcome these hurdles by using Rajan and Zingales (1998) methodology on dis-aggregate sector bilateral trade between developed and developing countries, and by controlling for the level of offshoring measured *à la* Acemoglu and Autor (2011). We evaluate empirically the effects of ICT[4] on the demand of imports that six developed countries, with a high level of investment on new technologies[5], sourced from 40 developing countries.

[4]For this, we consider ICT equipment which, as stated by the OECD, is "defined as computer and office equipment and communication equipment" and software (which includes both purchased and own account software). For now on we will refer to both of these components as ICT.

[5]We select developed countries with the highest level of ICT and industrial robots per 1000 workers.

We establish the causal impact of new technologies/computerization on the decline of developed countries' imports from developing countries by using three standard econometric approaches. First, as mentioned, we use Rajan and Zingales (1998) approach, providing evidence for a specific channel/mechanism through which, in this case, ICT works. The technologies embodied in new capital reduce the demand for specific occupations (i.e., OaRA) more than they do for others. Therefore, investment in this new type of tech capital, induced by a sharp fall in prices (in comparison with other capital, as can be seen in Figure 3), disproportionately replace tasks of occupations typically characterized by routine and non-routine tasks that new technologies can perform.

Figure 3: Evolution of Price Indexes for ICT and non-ICT equipment



Source: Own elaboration based on data from the U.S. Bureau of Economic Analysis (2023). Note: Price Indexes (2012=100, seasonally adjusted) for Private Fixed Investment by Type. In particular, for Equipment and information processing equipment (ICT) and software.

We use Autor et al. (2003) or Frey and Osborne (2017) to classify 788 occupations according to their automation risk by tech capital. The causality test then assesses whether imports of good produced by sectors characterized by a large share of employment in OaRAs, in developed countries at the beginning of our sample, show a lower growth rate than imports of others products after firms/sectors invest in new technologies. As a proxy for tech capital, we constructed an index using the information and communication technology (ICT) capital and software capital collected by the OECD (20 sectors). For robustness, we use and index for the aggregate and sectoral robot penetration as computed by the International Federation of Robots (IFR).

Second, to avoid any remaining reverse causality and following Acemoglu and Restrepo (2020), we use the average ICT adoption in other 14 developed countries as an instrument of tech capital in a given developed country. Developed imports from developing countries could be falling because of a shortfall in the supply of low wages or productivity in the latter countries. Developed countries react to this lack of supply of goods from developing countries investing in new technologies to produced these goods using a lower amount of employment of low wage occupations which are relative scarce in developed countries. The use of IV avoids this reverse causality.

Third, to avoid omitted variables, we control for bilateral-product and country-year fixed effects. The former sets of dummies control for initial conditions, and the second set control for import as well as export countries specific shocks during our sample period. Our identification comes from the relative changes of imports of products produced in sectors with a large share of employment in occupations subject to be replaced by new technologies. If developed countries imports of these products falls after they invest in new technologies, we can conclude that new technologies, now mainly adopted in developed countries, are reducing developing countries exports.

We find that imports in developed economies in industries with higher automation risk are (depending on the specification) between 19 to 25 percentage points lower, in 2016 than in 2000, for industries with higher ICT adoption. This indicates that the negative effect that computerization has by replacing low wage-labor is overcoming the positive effect that it generates in terms of higher production and demand for inputs from developing countries. Moreover, we find that a higher offshoring has a negative effect on imports, reducing them by 26 percentage points in countries with higher risk of computerization (impact that increased to 44 pp with our IV strategy). This is related to the fact that sectors susceptible to computerization are also probably more offshorable[6].

Hence, in the absence of large reallocation costs, countries-sectors that initially relocate production more, have greater incentives to implement technological changes reducing imports[7]. Based on these results, it is important to reassign resources from sectors that have been damaged by technological advances to other industries that will benefit from them. This should be follow with an adequate training of the labor force and development of human capital. The indicated, in order to allow developing countries to adapt to a new reality and complement future advances.

[6]However, this relationship is not 1:1. This means that there are works, like cashier, that can be automated but not offshorable (Frey and Osborne, 2017).

[7]The lower growth in GVC would be associated with a readjustment from firms after an intense period of offshoring in the late 1990's and beginning of the 2000's (Stapleton, 2019).

The rest of the paper is structured as follows: Section 2 presents the literature review associated with the effects of the adoption of new technologies (computerization/automation) on trade, and its relationship with offshoring. Section 3 describes the data sources and elaboration of the database used, along with the empirical strategy. Section 4 shows the main results derived from the estimates using OLS and IV methods. In Section 5 we report the results of several robustness tests with different measures of technology adoption and risk of automation, other estimation strategy (Pseudo Poisson Maximum Likelihood) and a sample of bilateral trade between high-income countries. Finally, Section 6 concludes.

2 Literature Review

2.1 Impact of automation on labor outcomes and trade

In the literature focused on the analysis of automation[8], several paper have documented the economic relationship between USA and Mexico. The study of Faber (2020) finds that robots in the United States would be associated with a reduction of jobs in Mexico as a consequence of lower exports. Pedemonte et al. (2019) and Artuc et al. (2019) reached a similar conclusion in terms of trade using a common empirical methodology, considering the exposure to local and foreign robots. Generally speaking, they used the variation in the stock of robots in terms of employment, weighted by the share of employment or exports (shift-share approach). Due to endogeneity concerns, the authors used as instrument (for robots in the United States) the stock of robots in other economies (rest of the world or european countries).

Acemoglu and Restrepo (2020) also study the impact of automation for the US. Using exposure to robots in a Bartik-style measure and an IV strategy (similar to the works previously mention) the authors find that one more robot per thousand workers reduces the employment-to-population ratio and wages. As instrument, they also used the stock of robots in european countries. Likewise, an with a similar IV approach, Micco (2019) study the impact of robots per workers on labor market outcomes and US imports. The results show that industries with a higher share of occupation at risk of automation (define using ALM and FO methodologies) have a lower rate of employment growth. Moreover, and for trade, imports in sectors with a higher participation of OaRA reduces to a greater extent from countries with lower automation.

Other study that evaluates the effects of automation as the exposure to domestic and foreign robots for a particular country, in this case Brazil, was made by Stemmler (2019). Using an IV approach, the author shows that foreign automation reduces employment in

[8]Here we review mainly literature that focus on automation as the used of industrial robots, due to it's similarities with the present investigation. Nevertheless, for a more extensive description of ICT literature (and it's effects on productivity and labor market outcomes) we recommend see Graetz and Michaels (2018).

manufacture and increased it in the mining sector. The former (latter) effect through the channel of final goods (input) exports. This would lead to a process of "premature de-industrialization" in emerging economies, highlighting the relevant effects that technological advances can have in these countries.

The analysis that evaluate the effects of automation[9] in trade using firm level data for specific countries is still scarce. Nevertheless, one of them was made by Stapleton and Webb (2020). Using an IV strategy and analyzing the case for manufacturing firms in Spain, the authors find that robots would have a positive effect on imports that spanish firms made from lower income countries. This is linked to the higher productivity associated with the new technologies implemented. However, there is heterogeneity showing that firms that were offshoring to lower-income countries before they started to use robots decreased the share of imports sourced from lower-income countries (in contrast to firms that had not already offshored).

There is also literature that focus on different groups of developed and emerging/developing countries. Diaz Pavez and Martínez-Zarzoso (2021) for 16 sectors, 10 emerging economies and using an IV approach find that only foreign robots (in contrast to local ones) have a negative effect on employment. In certain sectors this could be the result of a reduction in offshoring and potentially the fall in imports of final goods. Additionally, Micco (2019) finds, for 19 lead countries, that imports from Latin American economies have a lower rate of growth in sectors with a higher risk of automation. Particularly, sectors in the 90th percentile relative to the 10th percentile of the index created to proxy for risk of automation[10] have 29 percentage points lower imports from lead countries when we move from the 10th percentile of robot penetration to the 90th percentile.

Furthermore, Graetz and Michaels (2018) evaluate the effects of robots density (stock per million hours work) on labor productivity, total factor productivity, output prices and employment. This, for 14 industries and 17 countries over the period from 1993 to 2007. The authors, using two instruments[11], find that industry-country pairs that increased robot density experienced larger gains in labor productivity, increase TFP and reduce output prices,

[9]The authors consider three distinct automation technologies: robots, computer numerically controlled (CNC) machines and flexible manufacturing systems (FMS).

[10]This indicator is based on the classification that FO (2017) made for risk of automation at the occupational level. Two measures at the sector level were made (for the year 2004): i) the percentage of occupations that have an automation probability higher than 70% and ii) a weighted average (by employment) of the occupation automation probability.

[11]Using data on US occupations in 1980, the authors define occupations as "replaceable" if by 2012, their work could have been replaced, completely or in part, by robots. They then compute the fraction of each industry's hours worked in 1980 that was performed by occupations that subsequently became prone to replacement by robots. Their second instrument consider the extent to which industries used occupations requiring reaching-and-handling tasks (capability driven by technological supply factors) in 1980.

while there is no significant implications for aggregate hours worked (however, robots appear to reduce the relative share of hours worked by low-skilled workers).

Lastly, and most closely related to our work, Artuc et al. (2020), analyzing trade between "North-South" regions find that robots (in terms of working hours) actually increased imports and exports to less developed countries. This study uses 16 sectors defined under the "International Standard Industrial Classification" (ISIC, Rev.4)[12] and focus on 26 OECD countries and 181 non-OECD countries. To address the possibility of endogenity, the authors use two instruments: i) the triple interaction between the (pre-determined) share of workers engaged in replaceable tasks in each sector, the country's initial income per capita, and the global stock of robots and ii) trends in countries with similar income levels. This increased the positive effects found on trade.

In contrast, in the present investigation we consider 20 sectors under the same classification for ICT (our main measure of technology advances)[13] and 88 industries under a higher level of disaggregation using the "North American Industry Classification System" (NAICS) for imports and robots (in terms of employment) in our robustness analysis. This is important because it allows to identified the effects of computerization on imports in a clearer way. In addition, we directly consider the offshorability of industries in our main specification and a measure for probability of computerization that differs from their replaceability variable[14]. We also address the potential bias arising form the log-linear model using a Pseudo Poisson estimate as robustness, still finding a negative and significant effect on imports from developing countries.

2.2 Impact of automation on offshoring

Other works that focus on the consequences on offshoring are Carbonero et al. (2020)[15] and De Backer et al. (2018), finding that the use of robots in developed countries reduces offshoring, which in turn affects employment in developing economies. Also, as shown in the latter work, there is no evidence of reshoring (i.e. bringing activities, in particular

[12] By defining sectors in a more narrow way as in the case of our study, we expect to identify more precisely the effects of automation/computerization.

[13] It is important to note that IFR data has a series of limitations: about 30 percent of industrial robots are not classified into any industry, it does not cover industrial robots with only one industrial application, has incomplete coverage for a number of countries and assumes that robots do not depreciate for a period of 12 years losing all their value after that (Artuc et al., 2020).

[14] The authors assign a replaceability value of one to the occupation if the name and/or description contains at least one of IFR application categories and zero otherwise. At the industry level the measure considers the fraction of replaceable hours for each of the 16 robot-using industries.

[15] This study uses data for 15 sector between 2005 and 2014. The methodology is based in a different instrument to the one usually used in the literature. This is, an index of technological progress that accounts for the potential endogeneity of robots.

employment, that was once offshored back home to the developed economy). One explanation for this could be the growing importance in robotics (labor-saving). The results for offshoring of this investigation apply only for the period between 2010 and 2014, in which robot investment grew quickly. In this way, growth in the stock of robots in a 10% results in a decreased of -0.54% in offshoring growth (being the effect bigger in industries more labor intensive).

Krenz et al. (2021) carried out a study for a set of eastern european and emerging countries between 2000 and 2014 for 9 manufacturing industries. They find that an increase by one robot per 1000 workers is associated with an increased in reshoring of 3.4%, while using robots per million hours worked increased the effect to 5.1%. Both effects reduce to near 2.5% when using an IV approach. In a similar work Krenz and Strulik (2021) find that an increased in one robots per 1000 workers cause an increment in the reshoring intensity of 5.7% and 4% in eastern european countries and developing economies, respectively. In contrast, and increased in one robot per million hours worked results in an increment of 14.2% and 8.8% on the intensity of reshoring in the set of countries previously mention. Notwithstanding, there are no significant effects of automation on offshoring.

Finally, there is also a set of works that evaluate the consequences of offshoring, focusing on the effects on wages[16] and not in trade as the present investigation. Among these studies we find the one of Koerner (2021) for the manufacturing sector in Germany, with heterogeneous effects of offshoring depending if the destination country has high or low wages. In this last case, offshoring would be associated with and increased in german salaries in complex works. Likewise, Hummels et al. (2014) for Denmark and Oldenski (2014) for the United States find that offshoring reduces wages of unskilled workers and increased it for high-skill workers. This rised the premium by skill (or wage gap) within firms[17].

The innovation of the present work respect to the literature abovementioned[18] is that, first, focusing on developing countries, seeks to evaluate the effects of both computerization and offshoring on trade, which has not been empirically address. We implement a model with interaction terms similar to the one used in Rajan and Zingales (1998) in their influential work, where they establish that one way to make progress on causality is to focus on the theoretical mechanisms through which one variable affects the outcome of interest. We

[16]See Faia et al. (2021) for the effects of automation and offshoring on selectivity (measured by skill concentration, unemployment duration and educational mismatch). For 13 European countries, the author finds that sectors with higher initial automation (offshorability) experienced a differential increase (decreased) in selectivity. Measure for automation as in Acemoglu and Autor (2011) and offshorability as in Blinder and Krueger (2013).

[17]However, a productivity increased in firms could counteract this, enhancing exports and with this wages of both types of workers (Hummels et al., 2014).

[18]See Table 12 at the end of this document for a more extensive description of the main literature here presented.

also used an IV estimation to avoid any reverse causality and fixed effects to control for omitted variables. Besides, the relevant variables in the estimation differ from the ones typically used. Our main measure is an ICT index as proxy for technological advances (for 20 sectors). Additionally, we used industry measures for probability of computerization and offshorability based on the works of Autor et al. (2003) and Acemoglu and Autor (2011). Lastly, in terms of imports, they are disaggregated in 88 sectors, which allows us to identify the effects of new technologies unambiguously in comparison with previous literature.

3 Data Sources and Empirical Strategy

Information on bilateral trade, particularly imports (in USD) that developed economies sourced from developing economies, were obtained from the Atlas of Economic Complexity (2019). This database contains the value of transactions between countries at the product level defined at 4 digits using the "Harmonized System" (HS) for the year 1992. We evaluate the concordance of this product classification with "The North American Industry Classification System" (NAICS), ending up with 88 sectors at 4 digits of disaggregation.

The six countries considered as developed in this study are: France, Denmark, United States, United Kingdom, Japan and the Netherlands. These economies were chosen because they are high income countries[19] with ICT information at the aggregate and sector level, collected by the OECD. We used this data to construct our main ICT measure (an index) equal to the ICT stock in terms of it's 2000's level. We divided this by an equivalent employment index, created using data from the last version of the "World Input Output Database" (WIOD, 2016) which covers 43 countries in the world from 2000 to 2014 and 56 sectors[20] defined using the "International Standard Industrial Classification" (ISIC Rev.4).

As mention, data for sectoral ICT comes from the OECD (2022a), which is at constant prices (national base year). For this reason, we adjusted the information by exchange rates so every value is at US dollars. In addition to that, we implement a perpetual inventory method to complete the stock data when not available. For this, we used information on ICT investment also from the OECD and, as depreciation rate, we used the (underlying) values from sectoral ICT stocks for the US data.

Also, we choose our six developed countries because they have a high aggregate level of automation measure by the stock of robots per 1000 workers[21]. This is calculated using

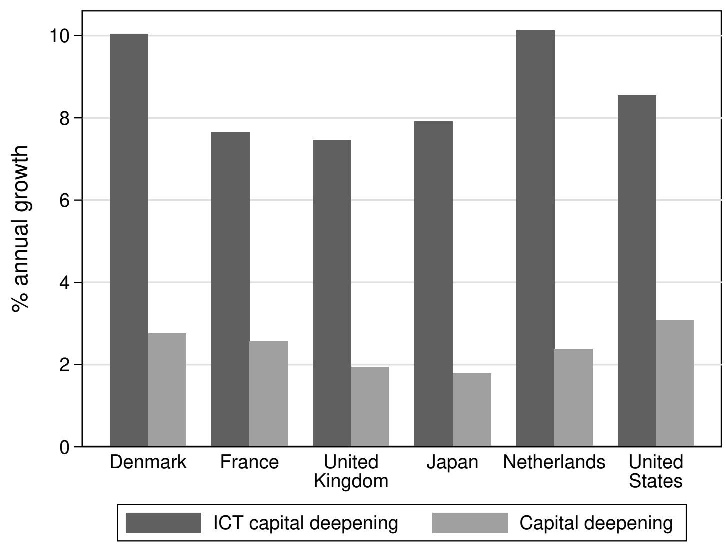
[19]They were in the "high income" category of the World Bank in the year 2000. This means that they had a gross national income per capita of 9,265 USD or higher.

[20]For more information about the WIOD database see Timmer et al. (2015). For the level of employment in the years 2015 and 2016 we consider the same growth rate for this variable as in 2014.

[21]This is represented in Figure 6 in the Annex 1, where we can see that Japan is the economy (in the

data from the International Federation of Robotics (IFR). According to this institution[22] industrial robots are "automatically controlled, reprogrammable, multipurpose manipulator, programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications".

Figure 4: Annual growth of ICT and Capital in developed countries



Source: Own calculations based on OECD (2022b) data. Note: Figure 2 displays the annual growth for ICT capital deepening and Capital deepening (meaning, both measures in terms of total hours worked).

Figure 4 shows the (mean) annual rate of growth for ICT capital and Total capital deepening (meaning, both measures in terms of total hours worked) for the six developed countries under analysis during the period between 2000 to 2016. We have that the first measure is significantly bigger, with an average annual growth close to 8.6%, being near four times higher than the same measure for Total capital per hour worked, of around 2.4%. This highlights the important adoption of new technologies in the last decades (particularly the ones that could replace routine tasks) by developed economies and why we focus on it's potential effects on trade.

sample) with the highest robot stock per worker, followed by Denmark and the Netherlands with rising trends in this measure. Figure 7 shows the significant difference in robot adoption between both groups of countries, which reflects the fact that automation is a recent phenomenon in developing economies.

[22]Based on the definition of the "International Organization for Standardization" (ISO).

3.1 Computerization and offshoring

Autor et al. (2003) task model suggests that routine tasks, both cognitive and manual, are prone to computerization. By contrast, non-routine cognitive analytic, interpersonal, manual/physical, or manual interpersonal tasks are difficult to automate. Frey and Osborne (2017) extends this idea and claim that computerization can be extended to any non-routine task that is not subject to any engineering bottlenecks. These authors collect the expert opinion of machine learning (ML) researchers to identify engineering bottlenecks.

Based on this, we borrow ALM (2003) method to classify 748 occupations according to the number of routine and non-routine tasks performed in 2010. These authors identify six types of tasks: routine cognitive, routine manual, non-routine cognitive analytic, non-routine interpersonal, non-routine manual physical, and non-routine manual interpersonal tasks. They argue that routine tasks, both cognitive and manual, are prone to automation. Using ALM codes, we constructed the previous six tasks' indexes using the O*NET 23 database and occupation employment data derived from OES 2010. To this end, the indexes are normalized to have mean 0 and variance 1. We constructed our automation measure at the occupation level as follows:

$$PROB_o^{ALM} = \sum_{\tau \in \, routine} T_\tau^o - \sum_{\substack{\tau \in \, Non \\ routine}} T_\tau^o$$

In the aforementioned equation, T_τ^o denotes the index for task τ in occupation o. Two of the tasks are routine and four are non-routine. Following Autor et al. (2003), who suggest that routine tasks, either cognitive or manual, are prone to computerization, the Routine Task Index ($PROB_o^{ALM}$) signifies a proxy for the probability that occupation o is at risk of computerization. For each sector, defined at 4 digit NAICS Rev.2007, we computed the employment weighted average of $PROB_o^{ALM}$. This is our main measure of sector j share of employment at risk of automation $PROB_j$.

For robustness, we constructed an alternative proxy for automation risk[23]. Frey and Osborne (2017) used an econometric method to assign the risk of automation (FO RISK Probability) to 702 occupations defined at the three- to six-digit level of the Occupational Employment Statistics (OES) 2010 BLS definition (OES 2010). We merged 698 of these occupations with the OES employment dataset, and we extend the number of occupations to 788. For each sector j, defined at 4 digit NAICS Rev.2007, we computed the employment weighted average of occupation FO RISK Probability ($RISK_j$). This is our robustness measure of sector characterized by employment in occupations at risk of automation.

[23]Construction of the variables for risk of computerization and offshoring based on the work of Micco (2019a).

An important aspect of the measures that we have to take into account is that they were created based on the idea of risk of automation for an occupation in a specific moment in time, which could (and probably) will change in the future. This, because the technological advances modify the degree of automation of different activities. This serve as a positive aspect, allowing the measure to be more exogenous. Nevertheless, an implicit assumption used here (more questionable) is that the weights of occupation per industry are similar between the United States (country from which comes the data on employment to create the measures) and the rest of developed economies under analysis.

Additionally, we borrow Acemoglu and Autor (2011) offshorability measure based on O*NET task measures and the work of Firpo et al. (2011), similar in structure to what we describe previously for our Routine Task Index ($PROB_j$). It consider seven O*NET scales (normalized)[24] and occupation employment data derived from the OES to create a composite measure equal to the summation of the respective constituent scales, then standardized to mean zero and standard deviation one. For each sector, defined at 4 digit NAICS Rev.2007, we computed the employment weighted average to obtain our main measure of sector j share of employment at risk of offshorability OFF_j.

Table 1: Descriptive Statistics

Variable	Obs	Obs zero	Mean	Standard deviation	Minimum	Maximum
PROB	355,113		1.91	0.89	-0.62	4.15
RISK	355,113		0.68	0.08	0.32	0.80
OFF	355,113		-0.04	0.28	-1.03	0.85
ICT	276,887		1.67	0.86	0.45	16.72
ln(IMP)	272,546	82,587	13.75	3.23	4.54	24.74

Note: PROB is our Routine Task Index based on ALM (2003) and RISK is the automation risk by FO (2017). OFF consider the offshorability at the industry level based on Acemoglu and Autor (2011). Variable "ICT" represents our index for ICT. Lastly, "ln(IMP)" takes into account the imports when the values are different from zero.

In the econometric section our sample use data from 40 developing countries in ATLAS[25].

[24] Face to face discussions, Assisting and Caring for Others, Performing for or Working Directly with the Public, Inspecting Equipment, Structures, or Material, Handling and Moving Objects and Repairing and Maintaining Mechanical/Electronical Equipment. Tasks with these attributes score low on the offshorability scale.

[25] The 40 countries included in this sample are: Argentina, Bulgaria, Bosnia and Herzegovina, Belarus, Brazil, Chile, China, Colombia, The Czech Republic, Egypt, Estonia, Hungary, Indonesia, India, Iran, South Korea, Lithuania, Latvia, Morocco, Moldova, Mexico, Malaysia, Oman, Pakistan, Peru, Philippines, Poland, Romania, Russia, Saudi Arabia, Serbia, Slovak Republic, Thailand, Tunisia, Turkey, Ukraine, Uzbekistan, Venezuela, Vietnam and South Africa.

Table 1 reports the summary statistics of our proxies for risk of automation[26] (at the 4 digit NAICS Rev.2007), offshoring, ICT and imports. We report only sectors that have bilateral import data in ATLAS trade dataset. The mean, standard deviation and min/max for bilateral imports (ln) only include data with positive imports (>0). In our econometrics exercises we use bilateral observation even when imports are zero. Column "Obs zero" describes the number of bilateral product observations which are zero. Table 2 report pair-wise correlation of previous measures. The correlation between our two measure of risk of automation is 0.77, between PROB and our offshoring proxy is 0.1150 and between this and FO measure (RISK) is -0.1517.

Table 2: Correlation between risk of automation measures and offshoring

Variable	PROB	RISK	OFF
PROB	1		
	(88)		
RISK	0.7700***	1	
	(88)	(88)	
OFF	0.1150	-0.1517	1
	(88)	(88)	(88)

Source: Own calculations. Note: Number of observations in parenthesis. Significant level *** p<0,01, ** p<0,05, * p<0,1.

Finally, to merge the previous information described with the one of bilateral trade we used a dataset that contains the concordances between NAICS and HS classification (Schott, 2008). We also check the equivalences for different versions of the HS classification across years, particularly the ones of 1992 (as in the trade database) and 2007 (associated with the information in the concordance base for NAICS-HS).

3.2 Econometric Model

First we study only the impact of new technology. We evaluate the effect that our index for ICT adoption has on imports sourced from developing countries by developed economies. This, as describe in the next equation:

$$ln(Imp)_{yjxt} = \alpha + \alpha_{xt} + \alpha_{yt} + \alpha_{yjx} + \delta_1 PROB_j ln(ICT)_{yjt} + \delta_2 ln(ICT)_{yjt} + \varepsilon_{yjxt} \quad (1)$$

Where y corresponds to one of the six developed countries (importers), x one of the developing countries (exporters), j corresponds to the 20 sectors for ICT defined by the ISIC Rev.4 classification (and, in the case of imports, one of the 88 NAICS sectors) and t identifies the year, for the period 2000 to 2016. The dependent variable is the logarithm of imports

[26] The negative relationship between this variable and imports is presented in Figure 8 in Annexes.

$(ln(Imp))$[27], whereas the independent relevant variable corresponds to the interaction between the Routine Task Index ($PROB$) and the logarithm of our ICT index ($ln(ICT)$) at the industry level (variable also included separately as can be seen in our Equation 1, but omitted in some tables of results for ease of exposition). We also considered a set of fixed effects by developed country-year (α_{yt}), developing country-year(α_{xt}), and bilateral trade-sector (α_{yjx}).

Besides our OLS estimation, we implement and IV strategy to account for the endogeneity of the variable *ln(ICT)*. The instrument, similar to what can be seen in previous literature, consider the mean of our ICT measure for other developed economies (not including the country that we are constructing the instrument for)[28].

In a second stage, we include in the previous estimation the interaction between the offshoring measure, risk of automation and ICT. We also include the interaction between offshoring and ICT, as can be seen in the following expression:

$$\begin{aligned} ln(Imp)_{yjxt} = \alpha + \alpha_{yt} + \alpha_{yjx} + \delta_1 PROB_j ln(ICT)_{yjt} + \delta_2 ln(ICT)_{yjt} \\ + \delta_3 OFF_j PROB_j ln(ICT)_{yjt} + \delta_4 OFF_j ln(ICT)_{yjt} + \varepsilon_{yjxt} \end{aligned} \tag{2}$$

Our main results are at the sector level but we also estimate the previous equations at the country level. In this case, we used a measure for ICT capital in terms of total hours worked (also known as ICT capital deepening), as an index with 2015 as the base year. As a final observation, all the variables, at the aggregated and sectoral level, are standardized (mean 0 and standard deviation 1). The effects are for the whole period under analysis.

For robustness we make five additional exercises: Firstly we evaluate Equation 1 using our second measure of risk of automation ($RISK_j$) based on the work of Frey and Osborne (2017). Secondly, we use another proxy for technological progress, and index (same structure as our main ICT measure) for the stock of robots, with data collected by the IFR. Next, we implement another methodology to account for the zero trade data using the Poisson Pseudo Maximum Likelihood estimation (PPML), which can be seen in Subsection 5.3. In a fourth step we evaluate the results at the aggregate level using non-ICT capital and Total Capital. Lastly, we evaluate the effects when considering the bilateral trade between the six developed economies previously described and other high income economies,

[27] More precisely, we use the logarithm of imports plus the minimum value of them (different from zero), so we are able to include observations with 0 trade value. We address the issues with this methodology in our robustness analysis.

[28] We consider all the high income countries, based on the World Bank criteria previously described, for which we have information available on the OECD database. In the case of the sectoral measure there are nine countries which are (besides our six developed economies): Austria, Belgium, Canada, Finland, Greece, Ireland, Italy, Norway and Sweden. For consistency, we also used these countries for the instruments in the robustness analysis.

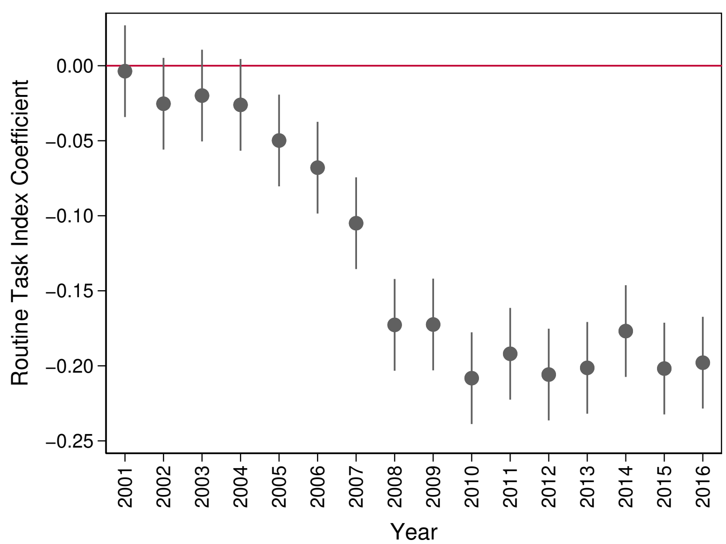
no longer with developing economies (see Subsection 5.5). In this last two exercises we expect effects of lower magnitude/opposite sign or with an insignificant impact.

4 Main Results

4.1 Effects of computerization on trade

Figure 5 shows that a higher risk of computerization (proxy by our Routine Task Index) in industries from developed countries is associated with a reduction in imports (relative to the year 2000) sourced from developing countries. However, these effects are not significant until 2005. After that, the impact on imports is significant and increasingly negative (a higher risk of computerization reduces imports to a larger extent)[29] specially post 2007. This is in line with the more flat trend in imports post the financial crisis[30] as illustrated in Figure 10 in Annexes.

Figure 5: Estimated Coefficient of Routine Task Index by year



Note: Estimation where the dependent variable is the logarithm of imports and the independent variable is the interaction between a dummy for year and ALM Routine Task Index (PROB). This standardized (mean 0, standard deviation 1). Fixed effects by developed country-year, developing country-year and bilateral-sector. 90 percent confidence interval.

[29] Figure 9 in Annexes shows the case for offshoring. The impact is significant after 2005, where more offshorable sectors have more imports, but the magnitude of the effect (mostly) decrease post 2008.

[30] Stapleton (2019) points out that since the crisis there was a stagnation in the growth of GVC, changing the behavior of international trade, reducing the one between high and low income countries.

Table 3 shows the results for the estimation of Equation 1 using our measure of ICT at the aggregated and sectoral level, along with the IV strategy. Importantly, the impact on imports is for the whole period of time under analysis, this is, the 17 years in the sample. We find that in the presence of an increased in one standard deviation in ln(ICT), imports in industries in the 90th decile for risk of computerization (PROB) relative to industries in the 10th decile are 22 percentage points lower (near 1.2 if we consider the annual growth rate). This with our aggregated measure and IV. The impact on imports is higher when using sectoral ICT, with a reduction of 25 percentage points (pp) increasing to 37 when we used our instrument (mean ICT index in other high income countries). If we evaluate what happens in an industry in the 80th decile relative to the 20th the reduction on imports is close to 12-18 percentage points for our sector measure depending on the specification.

Table 3: Equation 1 results- ICT

Variables	ln(imp) Aggregated	ln(imp) IV	ln(imp) Sectoral	ln(imp) IV
PROB*ln(ICT)	-0.0788***	-0.0784***	-0.0916***	-0.134***
	(0.00356)	(0.00362)	(0.00499)	(0.00778)
Dif. p90-p10 (PROB)	-0.22	-0.22	-0.25	-0.37
Dif. p80-p20 (PROB)	-0.10	-0.10	-0.12	-0.18
Observations	355,113	355,113	276,887	276,887
R^2	0.867	-	0.867	-
F-test (fist stage)	-	1,944,593	-	1,347
FE developed-year	✓	✓	✓	✓
FE developing-year	✓	✓	✓	✓
FE bilateral-sector	✓	✓	✓	✓

Robust Standard errors in parenthesis. Significant level *** p<0,01, ** p<0,05, * p<0,1
Note: Variable "ln(ICT)" corresponds to an index using ICT Capital deepening/stock of ICT for aggregated and sectoral measures, respectively. PROB is our Routine Task Index based on ALM (2003). Variables are standardized (with mean 0 and standard deviation 1). Fixed effects by developed country-year, developing country-year and bilateral-sector. Table shows the change in one standard deviation of "ln(ICT)" for the difference (dif) between sectors in the 90th decile and 10th decile for PROB (a similar analysis for the decile 80th-20th).

Table 3, along with the following results, presents the F-test of the first stage regression for each IV specification. This, because a standard approach/criterion to evaluate if an instrument is relevant is to look if the F-test is higher than 10, which occurs throughout our different regressions. Regarding the exclusion restriction, it is reasonable to think that ICT adoption in other high income countries is not correlated with trade outcomes (thus, only affects through the similar technological progress in advanced economies).

4.2 Incorporating the effects of offshoring on trade

The results for Equation 2 are show in Table 4. Now, we include the measures of offshoring described in Subsection 3.1. As can be seen, we have robust results for the interaction between our proxy for risk of computerization and ICT. This for the different specifications, with a negative and significant effect at 1% confidence level, similar in magnitude to what we found with Equation 1. Under our aggregated and sectoral estimate, an increased in one standard deviation in ICT decrease imports in 19 percentage points when we compare industries in the 90th-10th decile of PROB. In contrast, when we compare an industry in the 80th decile of risk of computerization relative to one in the 20th imports are 9 percentage points lower.

Table 4: Equation 2 results- ICT

Variables	ln(imp) Aggregated	ln(imp) IV	ln(imp) Sectoral	ln(imp) IV
PROB*ln(ICT)	-0.0702***	-0.0712***	-0.0710***	-0.119***
	(0.00496)	(0.00502)	(0.00720)	(0.00992)
ln(ICT)			-0.0959***	-0.325**
			(0.0244)	(0.136)
OFF*PROB*ln(ICT)	-0.0118***	-0.0109***	-0.0238***	-0.0414***
	(0.00276)	(0.00280)	(0.00383)	(0.00642)
OFF*ln(ICT)	0.0232***	0.0277***	0.0206***	0.0589***
	(0.00352)	(0.00357)	(0.00514)	(0.00772)
Dif. p90-p10 (PROB)	-0.19	-0.20	-0.19	-0.32
Dif. p80-p20 (PROB)	-0.09	-0.09	-0.09	-0.16
Observations	355,113	355,113	276,887	276,887
R^2	0.867	-	0.867	-
F-test (fist stage)	-	192,338	-	494
FE developed-year	✓	✓	✓	✓
FE developing-year	✓	✓	✓	✓
FE bilateral-sector	✓	✓	✓	✓

Robust Standard errors in parenthesis. Significant level *** p<0,01, ** p<0,05, * p<0,1
Note: Variable "ln(ICT)" corresponds to an index using ICT Capital deepening/stock of ICT for aggregated and sectoral measures, respectively. PROB is our Routine Task Index based on ALM (2003) and OFF is our sectoral offshorability proxy. Variables are standardized (with mean 0 and standard deviation 1). Fixed effects by developed country-year, developing country-year and bilateral-sector. Table shows the change in one standard deviation of "ln(ICT)" for the difference (dif) between sectors in the 90th decile and 10th decile for PROB (a similar analysis for the decile 80th-20th).

In the fourth column, with the IV strategy, the effects on imports is higher than the ones found at the aggregated and sector level without instrument. Under this last specification, an increased in one standard deviation in ln(ICT) reduce imports in 32 pp (comparing industries with high/low risk of computerization). This could be for a potential bias in our estimation due to reverse causality.

Lastly, in terms of the effects of offshoring, we have that the difference between sectors in the 90th-10th decile for PROB, in response to a change in one standard deviation in ln(ICT) -when sectors have one more standard deviation in offshoring - is 23 percentage points lower imports (impact that reduces to 11 pp when comparing industries in the 80th-20th decile for PROB). This for our aggregated measure with and without IV. When we consider our sectoral measure (OLS), the effect slightly increased to 26 pp lower imports when comparing the 90th-10th decile for PROB. With our IV strategy the effect of one standard deviation in offshoring is -44 pp imports.

5 Robustness

5.1 Using FO risk of computerization measure

Frey and Osborne (2017) task categorization is based on the work of ALM (2003) but, in comparison, they created an index with a forward looking view of the potential impacts of technology adoption and consider trends beyond the computerization of routine tasks. For example, truck driving was a non-routine task that with the future advances could be automated[31]. Thus, the authors identify which problems engineers need to solve for each occupation, and with this the susceptibility of jobs to computerization.

As a first robustness exercise, we evaluate Equation 1 using our second proxy for risk of computerization, RISK, based on the work of FO (2017) previously described (see Subsection 3.1). The results are half of the magnitude of the ones found in our main specification in Table 3. Now, under our aggregated and sectoral estimate, an increased in one standard deviation in ln(ICT) decrease imports in near 12 percentage points when we compare industries in the 90th-10th decile of PROB. This effects increased to 17 pp when we used an IV strategy for our sectoral data.

[31]The authors emphasized the rol of advances in Machine Learning and Mobile Robotics, along with the use of big data, on the ability of computer capital to substitute non-routine tasks.

Table 5: Equation 1 results- ICT, FO index

Variables	ln(imp) Aggregated	ln(imp) IV	ln(imp) Sectoral	ln(imp) IV
RISK*ln(ICT)	-0.0465***	-0.0473***	-0.0524***	-0.0766***
	(0.00349)	(0.00354)	(0.00476)	(0.00904)
Dif. p90-p10 (RISK)	-0.11	-0.11	-0.12	-0.17
Dif. p80-p20 (RISK)	-0.06	-0.06	-0.08	-0.11
Observations	355,113	355,113	276,887	276,887
R^2	0.868	-	0.867	-
F-test (fist stage)	-	989,126	-	1,185
FE developed-year	✓	✓	✓	✓
FE developing-year	✓	✓	✓	✓
FE bilateral-sector	✓	✓	✓	✓

Robust Standard errors in parenthesis. Significant level *** p<0,01, ** p<0,05, * p<0,1
Note: Variable "ln(ICT)" corresponds to an index using ICT Capital deepening/stock of ICT for aggregated and sectoral measures, respectively. RISK is our computerization risk based on FO (2017). Variables are standardized (with mean 0 and standard deviation 1). Fixed effects by developed country-year, developing country-year and bilateral-sector. Table shows the change in one standard deviation of "ln(ICT)" for the difference (dif) between sectors in the 90th decile and 10th decile for PROB (a similar analysis for the decile 80th-20th).

5.2 Using robot adoption

We estimate Equation 1 with another measure as proxy of technology adoption used in the literature, the stock of robots[32]. As can be seen in Table 6 the results again are negative and significant at 1% confidence, but lower. In the case of the aggregated measure, the impact is close to half of the one found in Table 3, with a decreased in imports of 14 pp. However, the IV results are similar. For the sectoral measures, the effects shrink considerably, being four times lower. Thus, with this variable, an increased in one standard deviation in robots decreased imports in 6 to 9 percentage points (without and with IV).

Albeit the impact on imports is lower with this measure, it support the idea that new technological advances that potentially replace labor (in particular, the ones intensive in routine task) have negative effects on imports. The magnitude in this case could be associated with the fact that industrial robots is a more recent advance in the area, therefore, has not been adopted on a large-scale yet (even in developed countries). For this reason, we can expect an increased in the impact of automation base on the use of robots in the future.

[32]The correlation between this variable an our ICT index is 0.40 (significant at the 1% level).

Table 6: Equation 1 results- Robots, FO index

Variables	ln(imp) Aggregated	ln(imp) IV	ln(imp) Sectoral	ln(imp) IV
RISK*ln(Robots)	-0.0611***	-0.104***	-0.0271***	-0.0414***
	(0.00473)	(0.00683)	(0.00723)	(0.0127)
Dif. p90-p10 (RISK)	-0.14	-0.23	-0.06	-0.09
Dif. p80-p20 (RISK)	-0.08	-0.14	-0.03	-0.05
Observations	355,113	355,113	341,787	341,787
R^2	0.867	-	0.868	-
F-test (fist stage)	-	308,651	-	30,747
FE developed-year	✓	✓	✓	✓
FE developing-year	✓	✓	✓	✓
FE bilateral-sector	✓	✓	✓	✓

Robust Standard errors in parenthesis. Significant level *** p<0,01, ** p<0,05, * p<0,1
Note: Variable "ln(Robot)" corresponds to an index using the stock of robots for aggregated and sectoral measures, respectively (using data from the IFR). RISK is our computerization risk based on FO (2017). Variables are standardized (with mean 0 and standard deviation 1). Fixed effects by developed country-year, developing country-year and bilateral-sector. Table shows the change in one standard deviation of "ln(ICT)" for the difference (dif) between sectors in the 90th decile and 10th decile for PROB (a similar analysis for the decile 80th-20th).

5.3 PPML estimation

In addition to our main specification, we estimate a Pseudo Poisson Maximum Likelihood (PPML) regression model. This is used as an alternative to multiplicative models where the dependent variable is nonnegative, as in the case here analyzed for trade. Unlike our log-linear model, PPML provides a natural way to deal with zero trade values[33] and, allows for consistent estimated parameters in the presence of heteroskedasticity (Correia et al., 2019). The results are presented in Table 7 for our aggregated and sectoral measures of technology adoption.

In this case, the effect of an increased in one standard deviation in ln(ICT) reduces imports between 8 to 10 percentage points (depending on the level of aggregation of the data), this when comparing the 90th-10th decile of computerization risk. The impact reduces to 5 pp when comparing the 80th-20th decile, and doesn't change with different fixed effects. This lower magnitude could be explain for the bias that arises in the log linear due to heteroskedasticity (related to Jensen's inequality) and the zero values in the dependent variable (included previously as lowest value of imports in the sample), which could have

[33] In the sample near 23% of imports have value zero.

rounding errors or be recorded as zeros when they actually are missing observations (Silva and Tenreyro, 2006).

Table 7: Equation 1 results PPML- ICT

Variables	imp Aggregated	imp Sectoral	imp Sectoral
PROB*ln(ICT)	-0.0280***	-0.0381***	-0.0381***
	(0.00591)	(0.00517)	(0.00959)
Dif. p90-p10 (PROB)	-0.08	-0.10	-0.10
Dif. p80-p20 (PROB)	-0.04	-0.05	-0.05
Observations	333,503	259,045	274,837
FE developed-year	✓	✓	✓
FE developing-year	✓	✓	✓
FE bilateral-sector	✓	✓	×
FE sector	✓	✓	✓

Robust Standard errors in parenthesis. Significant level *** p<0,01, ** p<0,05, * p<0,1
Note: Variable "ln(ICT)" corresponds to an index using the stock of ICT for the sectoral measure. PROB is our Routine Task Index based on ALM (2003). Variables are standardized (with mean 0 and standard deviation 1). Fixed effects by developed country-year, developing country-year and bilateral-sector. Table shows the change in one standard deviation of "ln(ICT)" for the difference (dif) between sectors in the 90th decile and 10th decile for PROB (a similar analysis for the decile 80th-20th).

5.4 Non ICT and Total capital

Table 8 shows the results of Equation 1 when controlling for non ICT capital. As can be seen, the effects for our ICT capital index are consistent with our main results. However, the impact of the non ICT capital and Total capital (columns one and three) are not significant. When using an IV strategy, the results are significant but positive and near a quarter of the effect of ICT capital.

This results match the hypothesis set out here. ICT capital is the main force causing a negative outcome in terms of trade between developing and developed countries. The reason for this is that ICT capital is associated with a reduction in production costs that allows developed economies to produce internally what previously was imported. As a consequence, low-wage countries are losing their comparative advantage to this technological progress that replace routine tasks.

Table 8: Equation 1 results- non ICT and Total Capital

Variables	ln(imp) Aggregated	ln(imp) IV	ln(imp) Aggregated	ln(imp) IV
PROB*ln(ICT)	-0.0783***	-0.0873***	-0.0827***	-0.0897***
	(0.00460)	(0.00495)	(0.00488)	(0.00504)
PROB*ln(Non_ICT)	-0.00114	0.0214**		
	(0.00672)	(0.00844)		
PROB*ln(K)			0.00856	0.0236***
			(0.00698)	(0.00762)
Dif. p90-p10 (PROB)	-0.22	-0.24	-0.23	-0.25
Dif. p80-p20 (PROB)	-0.10	-0.12	-0.11	-0.12
Observations	355,113	355,113	355,113	355,113
R^2	0.867	-	0.867	-
F-test (fist stage)	-	96,045	-	284,250
FE developed-year	✓	✓	✓	✓
FE developing-year	✓	✓	✓	✓
FE bilateral-sector	✓	✓	✓	✓

Robust Standard errors in parenthesis. Significant level *** p<0,01, ** p<0,05, * p<0,1
Note: Variable “ln(ICT)”, “ln(Non_ICT)” and “ln(K)” corresponds to an index using ICT Capital, non ICT capital and Total Capital (deepening), respectively. PROB is our Routine Task Index based on ALM (2003). Variables are standardized (with mean 0 and standard deviation 1). Fixed effects by developed country-year, developing country-year and bilateral-sector. Table shows the change in one standard deviation of “ln(ICT)” for the difference (dif) between sectors in the 90th decile and 10th decile for PROB (a similar analysis for the decile 80th-20th).

5.5 Bilateral trade between developed economies

Lastly, we estimate Equation 2 considering trade between our six developed economies. As shown in Table 9 we have that the effect of an increased in one standard deviation in ln(ICT) is positive and near a fifth of the effects found in our main results for our aggregated measures (see Table 3). This means a reduction in imports of 4 percentage points. The effect is positive, less significant and almost one tenth of the previous results when we used our sectorial measures (with and without the IV strategy). This confirms the hypothesis that automation in developed countries affects negatively imports from developing countries[34]. This as a consequence of the reduction in labor costs and incentives to local production.

[34] In Table 11 (Annex) we present the results using G7 countries and the 20 OECD founders. In both cases the effect now is negative and significant but a quarter/less than half of our main coefficients (respectively).

Table 9: Equation 1 results - Sample of developed countries

Variables	ln(imp) Aggregated	ln(imp) IV	ln(imp) Sectorial	ln(imp) IV
PROB*ln(ICT)	0.0125***	0.0132***	0.00996*	0.0153*
	(0.00404)	(0.00408)	(0.00583)	(0.00915)
Dif. p90-p10 (PROB)	0.04	0.04	0.03	0.04
Dif. p80-p20 (PROB)	0.02	0.02	0.01	0.02
Observations	44,846	44,846	34,977	34,977
R^2	0.950	-	0.950	-
F-test (fist stage)	-	54,950	-	69
FE developed-year	✓	✓	✓	✓
FE high income-year	✓	✓	✓	✓
FE bilateral-sector	✓	✓	✓	✓

Robust Standard errors in parenthesis. Significant level *** p<0,01, ** p<0,05, * p<0,1

Note: Variable "ln(ICT)" corresponds to an index using ICT Capital deepening/stock of ICT for aggregated and sectoral measures, respectively. PROB is our Routine Task Index based on ALM (2003). Variables are standardized (with mean 0 and standard deviation 1). Fixed effects by developed country-year, developing country-year and bilateral-sector. Table shows the change in one standard deviation of "ln(ICT)" for the difference (dif) between sectors in the 90th decile and 10th decile for PROB (a similar analysis for the decile 80th-20th).

Lastly, Figure 11 (Annex) shows the results obtained from Equation 1 when we leave out one developed/developing country at a time. Based on this we see that the interaction between PROB and ICT still has a negative and significant effect on imports. Nevertheless, we can see that the effect is slightly bigger (in absolute magnitude) when we exclude out of the sample the United Kingdom and Denmark (in the case of the developed countries) and lower when we exclude Belarus, Oman and Russia (in the case of the developing countries).

6 Conclusion

During the late 80's, the offshoring of production was the main strategy used by developed countries for reducing labor costs. However, technological advances in the last few decades have modified the structure of international trade. This is particularly relevant for the relationships established between advanced and developing economies. This, because countries that participated to a larger extent in offshoring are the ones that have more incentives to adopt the current technological changes. Also, this process has consequences in those developing countries for which offshoring was a central part of their developing process.

In view of the above, the paper presented assess the effects of computerization and offshoring (at the industry level) on imports of developed countries sourced from developing economies. We used a set of key variables: first, an index proxy for employment at risk of computerization (PROB), measure constructed based on the work of Autor et al. (2003). Second, we consider an index for ICT stock with data from the OCDE (2022a). Lastly, based on the work of Acemoglu and Autor (2011), we create an industry level measure for the employment that could be offshorable.

To identify a causal relationship, we use an OLS estimation with fixed effects at the country-year and bilateral-product level. In addition, we used an IV strategy to account for the possible endogeneity in our ICT variable. Following the literature, we constructed a measure based on the mean ICT index in high income countries. We also used Rajan and Zingales (1998) econometric approach, implementing interaction terms for our ICT and probability of computerization/offshoring measures. This, for a sample of six developed economies (choose for their high level of ICT adoption) and 40 developing economies.

The results found indicate that, in the face of an increased in one standard deviation in ln(ICT), imports in sectors in the 90th decile of risk of computerization (PROB) relative to an industry in the 10th decile are (depending on the specification, without and with offshoring) between 19 to 25 percentage points lower. These effects reduce between 12 to 9 percentage points when we compare what happens between an industry in the 80th and 20th decile for PROB. This effects are similar (although slightly lower) than the ones with an IV strategy. Furthermore, we have that before an increased in one standard deviation in offshoring, imports in a country in the 90th decile of risk of computerization relative to one in the 10th are between 26 to 44 percentage points lower (without and with IV).

Finally, the robustness analysis shows that the results are significant and negative, but of lower magnitude, when using our second proxy for computerization risk (FO measure) and our additional proxy variable to account for technological change (stock of industrial robots). The same is found when we use and PPML approach to account for the zero trade values in our data. The effect represents a 10 percentage point reduction in imports when comparing sectors in the 90th and 10th decile for risk of computerization. Lastly, we find that non ICT capital is not relevant when explaining the causes for the decreased in imports sourced from developing countries. Also, the effect is three to four times larger for this group of countries in comparison to high-income economies, where the impact of new technologies (from the trade channel) is smaller.

Based on these result, we argue that is relevant to implement public policies that allow developing countries to adapt to this new reality, looking for comparative advantages different to the ones that they previously had. Coupled with this, the training of workers is central for them to have the appropriate tools and skills to complement new technologies. In addition, it is necessary to reallocate resources between sectors facilitating the improvement of those that are affected positively by the current changes. In this way, they could adapt to the transformation process that is generating at a global level and modifying the trade relationships between countries.

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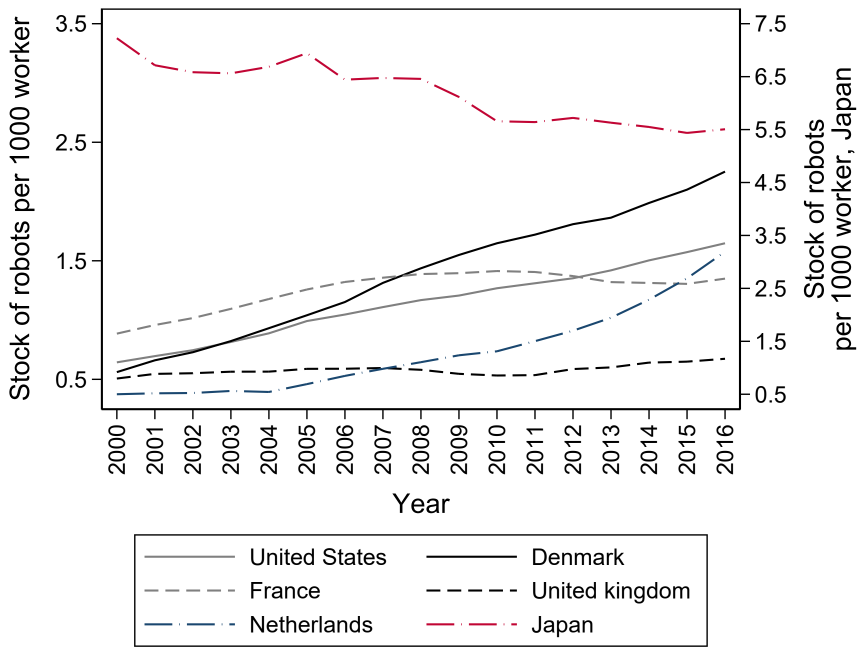
7 Annexes

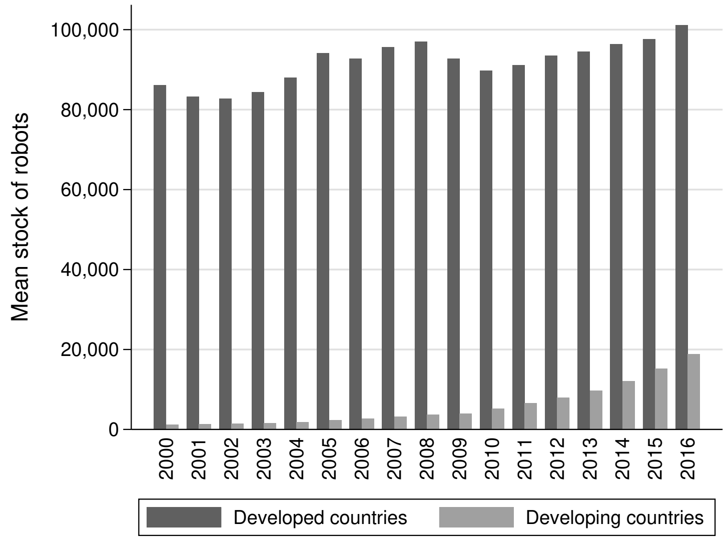
Annex 1

Figure 6: Stock of robots per 1000 workers evolution



Source: Own calculations. Note: Data on industrial robots is taken from the IFR and data on employment aggregated at the country level from the WIOD.

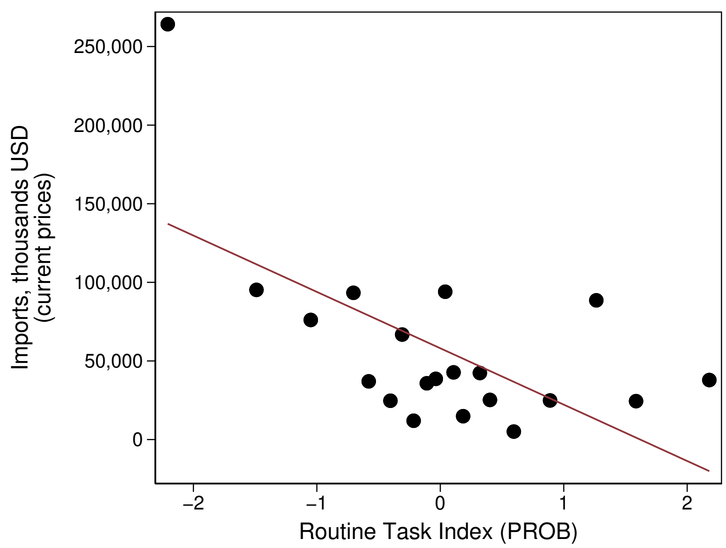
Figure 7: Mean stock of robots for developed and developing countries



Source: Own calculations. Note: Data on industrial robots is taken from the IFR. Average stock of robots for developed and developing countries in the sample.

Annex 2

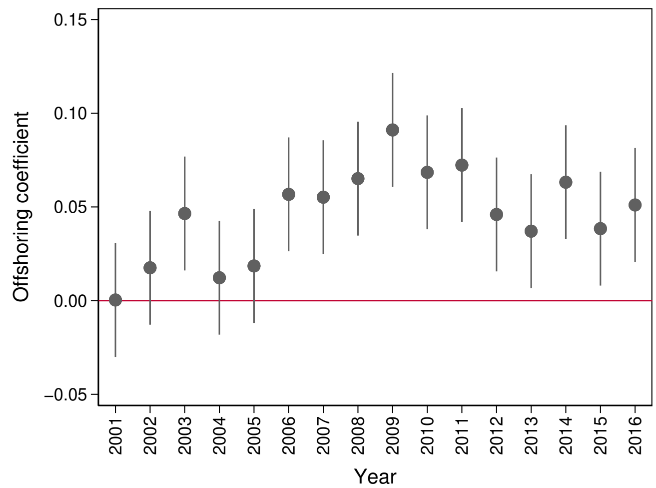
Figure 8: Relationship between imports and Routine Task Index



Source: Own elaboration. Routine Task Index (PROB) based on the work of Autor et al. (2003) (here standardized, with mean 0 and standard deviation 1).

Annex 3

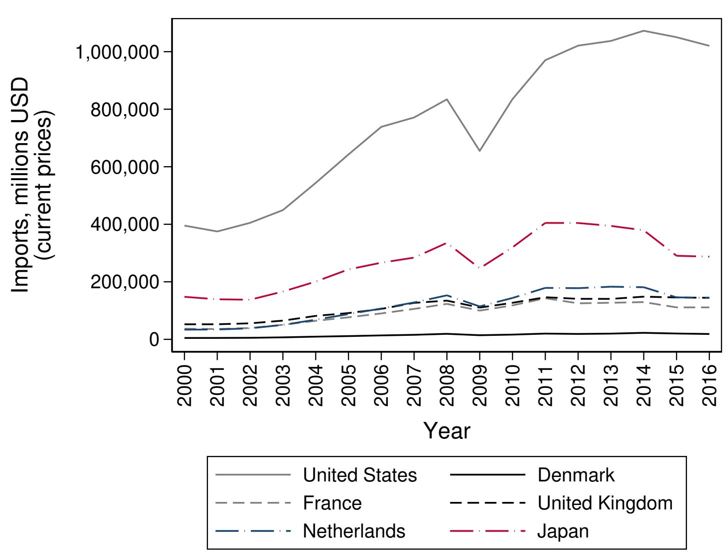
Figure 9: Offshoring effect on imports



Note: Estimation where the dependent variable is the logarithm of imports and the independent variable is the interaction between a dummy for year and our main offshoring measure (OFF), standardized (mean 0, standard deviation 1). Fixed effects by developed country-year, developing country-year and bilateral-sector. 90 percent confidence interval.

Annex 4

Figure 10: Import evolution from developing countries



Source: Own elaboration. Note: Data taken from the Atlas of Economic Complexity (2019).

Annex 5

Table 10: Equation 1 results - Sample of G7 countries

Variables	ln(imp) Aggregated	ln(imp) IV	ln(imp) Sectorial	ln(imp) IV
PROB*ln(ICT)	-0.0151***	-0.0155***	-0.0147***	-0.0330***
	(0.00359)	(0.00357)	(0.00498)	(0.00782)
Dif. p90-p10 (PROB)	-0.04	-0.04	-0.04	-0.09
Dif. p80-p20 (PROB)	-0.02	-0.02	-0.02	-0.04
Observations	56,814	56,814	44,222	44,222
R^2	0.957	-	0.957	-
F-test (fist stage)	-	300,087	-	264
FE developed-year	✓	✓	✓	✓
FE high income-year	✓	✓	✓	✓
FE bilateral-sector	✓	✓	✓	✓

Robust Standard errors in parenthesis. Significant level *** p<0,01, ** p<0,05, * p<0,1

Note: Variable "ln(ICT)" corresponds to an index using ICT Capital deepening/stock of ICT for aggregated and sectoral measures, respectively. PROB is our Routine Task Index based on ALM (2003). Variables are standardized (with mean 0 and standard deviation 1). Fixed effects by developed country-year, developing country-year and bilateral-sector. Table shows the change in one standard deviation of "ln(ICT)" for the difference (dif) between sectors in the 90th decile and 10th decile for PROB (a similar analysis for the decile 80th-20th).

Table 11: Equation 1 results - Sample of OECD countries

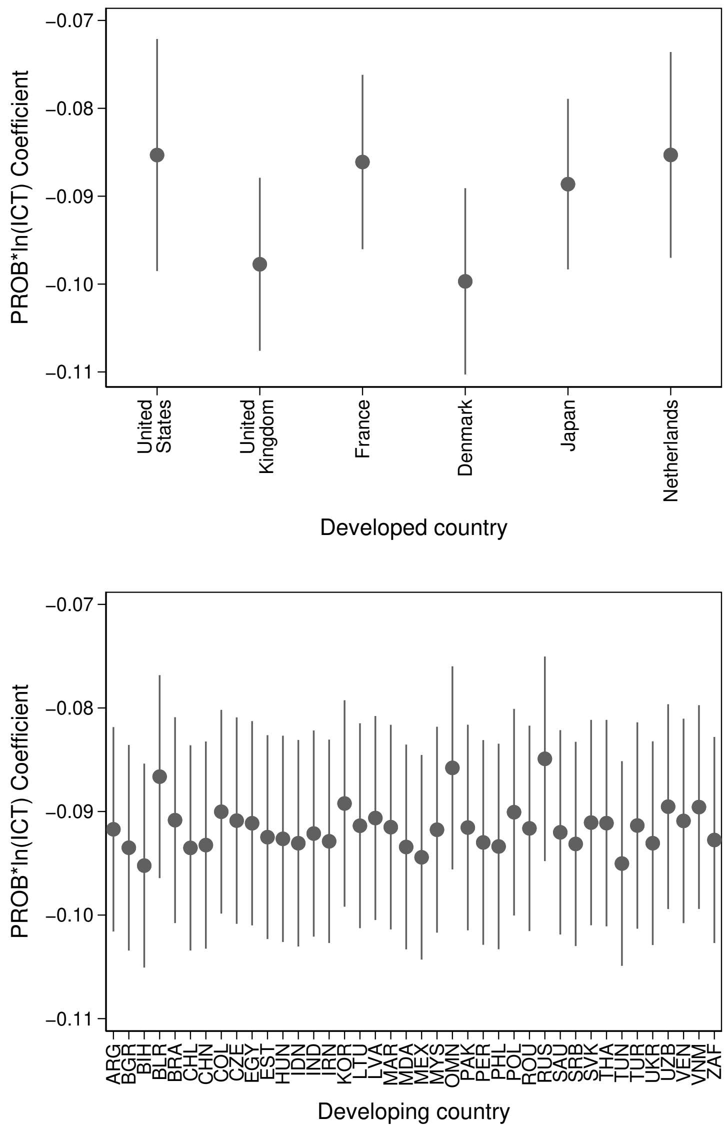
Variables	ln(imp) Aggregated	ln(imp) IV	ln(imp) Sectorial	ln(imp) IV
PROB*ln(ICT)	-0.0261***	-0.0265***	-0.0235***	-0.0520***
	(0.00281)	(0.00286)	(0.00395)	(0.00633)
Dif. p90-p10 (PROB)	-0.07	-0.07	-0.06	-0.14
Dif. p80-p20 (PROB)	-0.03	-0.04	-0.03	-0.07
Observations	162,605	162,605	126,585	126,585
R^2	0.935	-	0.934	-
F-test (fist stage)	-	881,749	-	672
FE developed-year	✓	✓	✓	✓
FE high income-year	✓	✓	✓	✓
FE bilateral-sector	✓	✓	✓	✓

Robust Standard errors in parenthesis. Significant level *** p<0,01, ** p<0,05, * p<0,1

Note: Variable "ln(ICT)" corresponds to an index using ICT Capital deepening/stock of ICT for aggregated and sectoral measures, respectively. PROB is our Routine Task Index based on ALM (2003). Variables are standardized (with mean 0 and standard deviation 1). Fixed effects by developed country-year, developing country-year and bilateral-sector. Table shows the change in one standard deviation of "ln(ICT)" for the difference (dif) between sectors in the 90th decile and 10th decile for PROB (a similar analysis for the decile 80th-20th).

Annex 6

Figure 11: Coefficients excluding one developed/developing country



Note: Figures show the results for Equation 1. Particularly, the coefficients for the interaction between our routine task index (PROB) and the ICT index. Developing countries in the same order as describe in footnote 25. 95 percent confidence interval.

Table 12: Literature Summary

Author	Data	Technique/Measure	Results
Artuc, E., Bastos, P., and Rijkers, B. (2020): Robots, tasks, and trade.	Panel data for the period 1995-2015. 16 sectors, 26 OECD countries and 181 non-OECD countries.	OLS and IV regression. Dependent variable: $log(1+imp)$. Independent variable: robot stock. Instruments: i) triple interaction between pre-determined country-wide labor costs, the share of workers engaged in replaceable tasks in the industry, and the global stock of robots ii) trends in countries with similar income levels.	10% Greater robot intensity leads to a rise (6.1%) in imports sourced from less developed countries in the same industry and an even stronger increase in exports (11.8%).
Artuc, E., Christiaensen, L., and Winkler, H. (2019): Does automation in rich countries hurt developing ones?: Evidence from the US and Mexico	Administrative data on Mexican exports by municipality, sector and destination from 2004 to 2014.	OLS and IV regression. Dependent variable: $\Delta log(exp/emp_{2000})$. Independent variable: increased in robots per thousand workers by sector in the US, weighted by the initial exports of each sector (respect to the total) at the local labor market level in Mexico in 2004. Controls for domestic automation. Instrument: exposure to automation in Europe (and Brazil for domestic automation).	An increase of one robot per thousand workers in the U.S. lowers growth in exports per worker from Mexico to the U.S. by 6.7 percent.
Carbonero, F., Ernst, E., and Weber, E. (2020). Robots worldwide: The impact of automation on employment and trade	Country-industry panel, from 2005 to 2014. 41 countries (WIOD) and 15 sectors.	OLS and IV regression. Dependent variable: $ln(L)$ and offshoring measure as share of imported non-energy inputs from emerging countries in total non-energy inputs. Independent variables: log of robot stock (cross-sector trend), dummy for labor intensity at the beginning of the sample period and the interaction between both. Instrument: index of technological advancement at the extensive margin (inverse of the standard deviation of the share of robots in each application).	Robots have a negative impact on worldwide employment. While it is small in developed countries, for emerging economies it amounts to -11% between 2005-2014. Robots in developed countries decrease offshoring just as employment (-8%) in emerging economies.

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Table 12: Literature Summary (Continued)

Author	**Data**	**Technique/Measure**	**Results**
De Backer, K., DeStefano, T., Menon, C., and Suh, J. R. (2018). Industrial robotics and the global organisation of production.	Data from 2000 to 2014. 40 countries.	OLS regression. Dependent variable: share of imported intermediate goods and services, over the sum of intermediate goods and services (excluding energy intermediate inputs). See Feenstra and Hanson (1996). Independent variables: annual growth in robot stock, labor intensity and the interaction. Analysis separately for developed and emerging countries.	The use of industrial robots (10% growth) in developed economies appears to be slowing the offshoring rates (-0.54% growth). However, the effect is not yet apparent in developing countries.
Diaz Pavez, L. R. and Martínez-Zarzoso, I. (2021). The impact of local and foreign automation on labor market outcomes in emerging countries.	Panel dataset from 2008 to 2014. 16 sectors (ISIC Rev.4), ten emerging countries and thirty developed economies (from WIOD).	OLS and IV regression. Dependent variable: total number of employees (in thousands), real wage per worker and capital stock. Independent variables: stock of local robots, exposure to foreign robots (shift-share measure, with weights as the ratio of exports over the total exports- for non-energy inputs- from emerging to developed countries, see Feenstra and Hanson (1996)) and inshoring (sectoral exports over total production from emerging to developed countries), all in logs. Instrument: number of robots from the two countries with the most similar output share (for local robots).	The results show that only foreign robot adoption, but not local, has affected employment (this could be driven by the reduction of offshoring), whereas no effects on the labor share and wage per worker are found.
Faber, M. (2020). Robots and reshoring: Evidence from mexican labor markets.	Data from Mexican local labor markets (commuting zones, CZs) between 1990 and 2015.	OLS and IV regression. Dependent variable: employment to population ratio/changes in exports. Independent variables: exposure to local/foreign robots (stacked differences) in terms of employment (weighted by the share of employment). Foreign exposure consider offshorability (share of Mexican imports in total US output). Instruments: robot adoption in the rest of the world (for robot adoption in Mexico and the US) and an index of offshoring (for the share of Mexican imports), as in Feenstra and Hanson (1999).	Consistently with reshoring as a mechanism, the results show that the negative employment effect (of US robots) is mirrored in similarly large reductions in Mexican exports and export-producing plants.

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Table 12: Literature Summary (Continued)

Author	Data	Technique/Measure	Results
Pedemonte, M., Vishwanath, T., and Zarate, R. D. (2019). Trade, robots and automation: The impact of us robots on labor outcomes in developing countries.	Robot data for the years 2004/2011-2014. Labor outcomes data (IPUMS) from the Mexican census of 2000 and 2015.	OLS and IV regression. Dependent variable: employment to population ratio and log earnings. For trade, exposure to net exports (difference between 2004-2014 in terms of employment) as a shift-share measure (weight by the labor share). Independent variable: exposure to US robots at the municipality level (same structure as net exports). Instrument: change in robots from other countries instead of the US.	Negative association between net exports stemming from Mexico and robots adopted in the US and a positive correlation between Mexican labor outcomes and net exports.
Stemmler, H. (2019). Does automation lead to de-industrialization in emerging economies?- evidence from brazil.	Trade data from WIOD and Comtrade database. 21 industries after crosswalks (own classification). Local labor markets as microregions (558) in Brazil. For the effects of foreign automation on exports all countries in WIOD database are used.	IV regression. Dependent variable: employment to population ratio. Independent variables: exposure to domestic/foreign automation as the yearly sectoral stock of robots per 1000 workers (weighted by the initial share of employment and additional measures if it's trade in inputs/final goods). Instrument: Average stock of robots in other developing countries. Controls for (among others): A routine task intensity index and changes in offshoring behavior of foreign companies (as the share of foreign owned enterprises).	Foreign automation is found to decrease manufacturing employment through the channel of final goods exports, while it increases employment in the mining sector through the channel of input exports.
Acemoglu, D. and Restrepo, P. (2020). Robots and jobs: Evidence from us labor markets.	Data for 722 commuting zones covering the US continental territory and 19 industries (between 1993/2004-2007).	OLS and IV regression. Dependent variable: variation in logs of employment and wages. Independent variable: Exposure to robots is thus a Bartik-style measure combining industry-level variation in the usage of robots and baseline employment shares. Instrument: robots in European countries that are ahead of the United States in robotics technology.	One more robot per thousand workers reduces the employment to-population ratio by 0.2 percentage points and wages by 0.42%.

Source: Own elaboration. Note: We present the literature which follows closely our work (for the sake of brevity, relevance and comparison). For this, we don't mention all the results of each author, but only the ones that are related to our study.