Computerization, Offshoring and Trade: The effect on Developing Countries

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Abstract

Antràs (2020) argues that whereas in the 1990s it was profitable to fragment production processes, now computerization allows the automation of human tasks, reduces labor costs, and substitutes the offshoring of certain activities. We analyze imports from six developed countries sourced from developing countries to study this hypothesis. We find a decline in imports of products from sectors characterized by low wages and routine tasks, therefore at risk of automation. Moreover, imports rose within sectors known for having a significant potential for offshoring until 2001, followed by a subsequent decline. Labor-replacing tasks technologies are changing the comparative advantages of developing economies.

Keywords: Trade, Computarization, Comparative Advantages, Developing Countries

1. Introduction

In the 1980s, there was a substantial rise in the fragmentation of production processes worldwide, also known as offshoring. This trend was facilitated by the information and communication technology (ICT) revolution, which expanded global value chains. Simultaneously, the reduction in trade barriers and costs, combined with the adoption of market economy systems, further strengthened the process of globalization. However, this phenomenon may be changing in the last decades which could alter its course (Antràs, 2020).

At first, the widespread adoption of information technologies allowed businesses to lower costs by moving their production operations to developing nations. However, the rise of innovative computerization technologies has introduced an alternative to offshore outsourcing. Recent studies demonstrate that computerization displaces routine tasks and reduces labor costs in developed countries (Autor and Handel, 2013; Goos et al., 2014, among others). Most recently, new literature indicates that robotics and artificial intelligence are increasingly taking over tasks previously performed by humans (Acemoglu and Restrepo, 2020a; Webb, 2020; Acemoglu and Restrepo, 2021). These technologies allow companies to substitute routine tasks, which are more commonly found in low-wage jobs (characterized by lower human capital). Consequently, as the literature suggests (Antràs, 2020; Krenz et al., 2021), this development can influence the decision-making process between computerization/automation and offshoring, altering the comparative advantages of less developed countries.[1]

[1]This decision depends on several factors, including labor supply conditions, access to credit, regulations in labor markets, aging of the population, among others (Stapleton and Webb, 2020; Krenz et al., 2021; Bonfiglioli et al., 2020 and Acemoglu and Restrepo, 2021).

Figure 1a- illustrates the negative correlation between (ln) occupation-wage and how prevalent routine tasks are in each occupation (a measure of "automatability" à la Autor and Handel (2013)). The simple pairwise correlation between the (ln) monthly and hourly occupation-wage and the occupation-level measure of automatability is -0.29 and -0.39, respectively. Reassuringly, Figure 1b- reports the same negative correlation using the probability of automation/computerization according to Frey and Osborne (2017). Contrary to these strong correlations, Figure 1c- shows there is not a strong correlation between occupation-wage and the occupation-level measures of "offshorability" as in Blinder and Krueger (2013).

Developed countries are driving the adoption of new technologies due to their access to financial capital, population aging, and higher labor costs. Therefore, developing countries that specialize in goods and services produced by low-wage routine task occupations may be losing their comparative advantages.[2] Figure 1d- illustrates the correlation between income per capita and the World Bank Digital Adoption Index (DAI).[3]

Nevertheless, it is noteworthy that developing nations have started to gain from the progressions in computerization/automation technologies, as these advancements are correlated with amplified capital accumulation and productivity levels in developed countries (Acemoglu and Restrepo, 2018).

[2]See Rodrik, 2018; Antràs, 2020; Acemoglu and Restrepo, 2021, among others.

[3]The DAI is a composite index measuring the extent of the spread of digital technologies within and across countries. The analytical underpinning for DAI is provided in World Bank Group (2016).

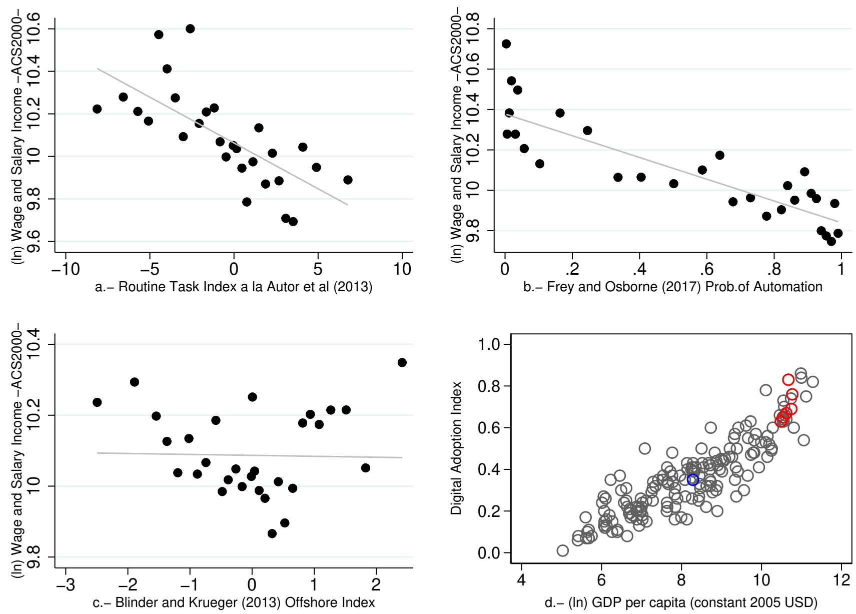

Figure 1: Correlation between wages - computerization/offshoring indices and, digital adoption in developed countries

Note: Routine Task Index from Autor et al. (2003) proxies the probability of computerization at the occupational level. Data on wages for the United States in the year 2000 (from the ACS). Probability of computerization/automation from Frey and Osborne (2017). Offshoreability Index from Blinder and Krueger (2013) at the occupational level. Digital Adoption Index (DAI) is a composite index measuring the extent of the spread of digital technologies within and across countries from the World Bank Group (2016). We show in red the six developed countries that we use in this paper.

As efficiency levels and capital grow in the aforementioned economies, a scale effect may ensue, resulting in an escalated demand for intermediate inputs from developing nations (Antràs, 2020; Artuc et al., 2019).

To summarize, **a sector** specializing in goods and services produced by low-wage routine task occupations in a developing country may lose demand due to the direct effect of computerization/automation in the North, while simultaneously benefiting from scale and income effects. The latter requires a large enough productivity increase in developed countries and the new demand for inputs to be for the same industry.

There is a dearth of conclusive empirical evidence concerning the impact of technological advancements on trade flows from developing countries. Most previous empirical studies have predominantly focused on examining the influence of these technologies on employment and wages within developed economies.[4]

The main purpose of this study is to provide evidence on how computerization/automation technologies affect the dynamics of North-South trade. The specific focus is on investigating whether developed nations' adoption of these technologies reduces the comparative advantages of developing countries in low-wage sectors that involve routine tasks. This study employs a partial equilibrium analysis, which means it does not consider the overall impact on exports in less developed countries.

The changes in comparative advantages, even when total exports increase, require resource reallocation and the implementation of policies to support this transition. The study aims to shed light on the implications of technology adoption for trade dynamics and the potential need for policy adjustments in response.

[4] See Autor and Handel, 2013; Autor et al., 2015; Acemoglu and Restrepo, 2020a and Ing, 2023.

We evaluate the effects of investment in Information and Communication Technology, which includes computer and software (from now on ICT capital)[5] on the demand for imports that six developed countries[6] sourced from more than 150 developing countries in 88 sectors during the period 1995 and 2018.

We establish the causal impact of new technologies/computerization on the composition of developed countries' imports from developing countries by using three standard econometric approaches.

First, we use Rajan and Zingales (1998) approach. Due to a higher elasticity of substitution, the technologies embodied in this type of new capital reduce the demand for occupations characterized by routine tasks more than they do for others. Therefore, a sharp fall in price in this type of capital, ceteris paribus, benefits more sectors with a large share of employment in occupations typically characterized by tasks that new technologies can perform. The relative price of ICT capital fell by 80% for industrial equipment between 1995 and 2022, inducing a huge change in the relative size of ICT capital and total machinery.[7] By exploiting the channel through which new technologies should affect trade, we make it more difficult for spurious cor-

[5]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).

[6]We select developed countries with available sector-level information of ICT and software.

[7]See "Table 5.3.4. Price Indexes for Private Fixed Investment by Type" from the Bureau Economics Analysis.

relations to drive results. For such a correlation to exist, both the measure of "risk of automation" and our instrumented measure of new technologies investment would need to be spuriously correlated in the "right" direction.

We use Autor et al. (2003) or Frey and Osborne (2017) to classify occupations according to their computerization/automation risk by tech capital. From now on we name occupations with high risk as Occupations at Risk of Automation (OaRA). The causality test then assesses whether imports of goods produced by sectors characterized by a large share of employment in OaRA (in developed countries at the beginning of our sample) show a lower growth rate. This is in comparison with imports of other products after sectors invest in new technologies. As a proxy for tech-capital, we constructed an index using the ICT and software capital collected by the Organization for Economic Cooperation and Development (OECD) across 31 sectors (25 of them tradable) in our six developed economies.[8]

Second, to avoid any remaining reverse causality and following Acemoglu and Restrepo (2020b), we use as an instrument for each country-sector tech-capital the average of ICT adoption in nine different developed countries.[9] Developed countries' imports from a developing country could be falling because of a shortfall in the supply of low-wage labor or due to negative productivity shock in the latter country. Developed countries react to this negative

[8]We assign the estimated ICT capital penetration in these 25 tradable sectors to the 88 sectors used in our trade model.

[9]Not all 10 countries have capital data in each sector over time.

shock by investing in new technologies to produce these inputs at home. The use of IV avoids this reverse causality.

Third, to avoid omitted variables, we control for bilateral-product, importer-year, and exporter-year fixed effects. The former sets of dummies control for initial conditions and the second and third sets control for importer and exporter country-specific shocks.

Our identification comes from the relative changes in 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 fall relative to others, after they invest in new technologies, we can conclude that new technologies adopted in developed countries are reducing developing countries' exports in sectors characterized by OaRA relative to the others.

We find a decline in imports of developed economies in products from sectors characterized by a high concentration of routine tasks. This decline is particularly noticeable in sectors that have embraced advanced ICT adoption. One standard deviation increase in ICT penetration reduces imports in a sector with one standard deviation higher index of routine tasks by 14-40%, vis a vis the average sector, between 1995 and 2018. This implies a 0.7-2.2 percentage points lower average annual import rate of growth during the whole period.

Moreover, our findings reveal that imports of products from sectors with a high index of offshorability, following the approach of Blinder and Krueger

(2013), have been on the rise, especially in those sectors that exhibit a higher adoption of new technologies, up until the year 2001. Confirming Antràs (2020), we observe that the relative imports of these products started to decrease after 2002. During the first seven years in our sample, one standard deviation increase in ICT penetration increases imports in a sector with the index of offshorability above the median by 18%, vis a vis the average sector. Between 2002 and 2018, one standard deviation increase in ICT penetration reduces imports, in the same sector, by 9%.

We do not find evidence that imports from sectors with a high risk of computerization and offshorability at the same time have a higher elasticity with respect to ICT penetration. Overall, the labor-replacing technologies that are primarily affecting low-wage occupations are changing the comparative advantages of developing economies.

Our paper contributes to a novel empirical literature that investigates the influence of new technologies on trade. The existing literature, which focuses on cross-country[10] and within-country evidence[11], does not offer conclusive evidence (See Section 2 for the Literature Review).

Prior papers have concentrated on robot adoption, which is undoubtedly significant for very recent years and the future. However, it represents only a tiny fraction of equipment investment over the past few decades, and that

[10]Artuc et al., 2020; Krenz et al., 2021; De Backer et al., 2018 and Carbonero et al., 2020.

[11]Stemmler, 2019; Faber, 2020; Stapleton and Webb, 2020; Bonfiglioli and Papadakis, 2023.

proportion becomes even smaller when considering intellectual property -software-. Benmelech and Zator (2022) show that the implied expenditure of investment in robots is small for European countries and the United States. Hence, it is about €11 /worker per year during 1993 and 2016, a very low figure compared to investment in software and data and ICT equipment which are €1,722/worker and €848/worker, respectively. Even in the last year of their sample, investment in robots is petite. Reassuringly, Furusawa and Sugita (2023) show that even though world trade in robots, a proxy for investment in robots, has steadily increased since approximately 2000, it still occupies a tiny portion (0.3% in 2018) of world trade in capital goods.

This paper advances this literature on two fronts. First, it uses the canonical idea that occupations characterized by routine tasks are the ones prone to automation/computerization, and the fact that these occupations have low wages. Therefore sectors initially characterized by the use of these occupations should be the ones that take more advantage of the fall in the price of computers in developed countries. Then imports from these sectors should fall from developing countries.

Occupations characterized by tasks prone to be replaced by robots, measured by the replaceability indexes used by previous studies based on Graetz and Michaels (2018b), have a weak negative correlation with low wage-occupations, -0.05 not significant with monthly wage and -0.16 with hourly wage. The same correlation for the Routine Task Index is -0.19 and -0.39

respectively,[12] Therefore, it is less clear that the fall in robots' price should change developing countries' comparative advantages, and therefore reduce imports from less developed countries. Also, as already mentioned, robot is still a tiny fraction of firms' investment, and therefore, it is less clear that they could have reshaped trade in the last decades. Second, the paper uses data from six developed countries' imports from more than 150 less-developed countries in 88 sectors. This allows us to study at the same time the role played by computerization/automation in imports from sectors characterized by occupations that are most vulnerable to technological change and offshoring. The rest of the paper is structured as follows: Section 2 presents the Literature Review. 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, Pseudo Poisson Maximum Likelihood and IV methods. Section 5 shows robustness results, obtain redoing the estimation excluding some countries from the sample and using Frey and Osborne (2017) index for computerization. Finally, Section 6 concludes.

2. Literature Review

Over the past few years, a new wave of empirical research has emerged, aiming to address whether the adoption of labor-replacing new technologies in

[12]The correlation between the sector replaceability index and the (ln) sector average wage is 0.01.

developed countries poses an opportunity or a threat to developing economies in terms of trade. Almost all of this literature focuses on robot penetration.

Artuc et al. (2020) find that greater robot adoption in the developed world leads, on average, to a rise in imports from developing countries. Following Graetz and Michaels (2018b), they constructed an industry-level replaceability index of employment using information on robot applications from the "International Federation of Robotics" (IFR). They use this sector index as an instrument for sector robot adoption after a fall in its price. Contrary to our results, a 10 percentage point increase in robot adoption in a sector in a developed country increases 6.1 percentage points in imports from non-OECD countries in this same sector.[13] We argue that their results solely reflect the productivity effect of the adoption of new technology and not changes in comparative advantages coming from lower wages. Contrary to our sector measure of employment in OaRA, the correlation between the Graetz and Michaels (2018b) replaceability index and wages is positive or zero (see Table 1), therefore the effect should not vary more across levels of development. Reassuringly, Artuc et al. (2020) finds that robotization in the North significantly promotes both imports from low and high-income non-OECD countries.

[13] The IFR defines different applications of robots. Using information about the description of each occupation, Artuc et al. (2020) assign a replaceability value of one to a three-digit occupation if the description included in it contains at least one of the IFR applications of robots and zero otherwise. The sector index is the sum of hours in occupations with a replaceability index of one divided by the total number of hours worked in the sector.

Krenz et al. (2021) show a positive association, although not always significant at the standard level, between robot adoption in European countries and the reshoring of production in 9 manufacturing sectors from around 40 developed and developing countries.[14] This finding aligns with the notion that increased robot penetration leads to reduced imports, as it prompts the reshoring of previously offshored production. They do not report results for offshoring from developing countries alone, therefore we cannot see the impact of robots on the comparative advantages of developing countries.

De Backer et al. (2018) indicate that the use of industrial robots in developed economies appears to be slowing the offshoring rates only in the last four years of their sample (2000-2014).[15] The authors do not study the differential effect of industrial robots in developed economies on imports from high, medium, or low-income countries.

Carbonero et al. (2020) finds weak evidence for the role of robot adoption on the share of imported non-energy inputs from emerging countries in total non-energy inputs. They find a negative coefficient, statistically significant at a 10% level, for the sector stock of robots in developed countries but positive, although not significant at standard levels, for the interaction term between the stock and sector labor intensity. This latter coefficient should

[14]Their broad measure of reshoring is then given by $R_{st} = \frac{DI_{st}}{FI_{st}} - \frac{DI_{st-1}}{FI_{st-1}}$ with the restriction that $R_{st} > 0$. Where DI and FI are domestic and foreign inputs used in sector s respectively.

[15]They measure offshoring as the share of non-energy imported intermediate inputs in total nonenergy intermediate inputs.

be negative if robots are used to perform labor-intensive tasks previously outsourced from developing countries.

Studies focusing on a specific country do not provide conclusive evidence either. Stemmler (2019) finds that exposure to foreign robot adoptions affects local employment in Brazilian manufacturing. For each local market in Brazil, the author computes the weighted average robot adoption of their importer partner. He finds that foreign robots affect local exports, although these results are not robust in all his econometrics models, and also they switch signs.

Closer to our study, Faber (2020) finds that exposure to U.S. automation, measured by robot adoption, contracts exports and labor market conditions in Mexico. Following Acemoglu and Restrepo (2020a), the author computes the penetration of robots in the US and non-US destinations of Mexican exports. He finds a negative and significant correlation between the penetration of foreign robots and export growth to the US, and a negative but small coefficient, in absolute value, and not always statistically significant correlation with export growth to non-US markets. The author claims that it is reassuring that foreign robot penetration reduces Mexican exports mainly to the US because it had a high initial offshorability.

Using Spanish manufacturing firms from 1990 to 2016, Stapleton and Webb (2020) find that firms that were importing intensively from lower-income countries before they started to use robots do not reduce the value of imports from developing countries but that the share they represent falls. By contrast, they find that in firms that started using robots before importing intensively from lower-income countries, robot adoption increases imports from these countries. Their results suggest that robot adoption caused firms to expand production and increase labor productivity and TFP. The scale effect increases input imports from all countries.[16]

Bonfiglioli and Papadakis (2023) study the effect of industrial automation (robot adoption) between 1990 and 2015 on US local labor markets and how it relates to offshoring. In line with our results, they find that robot adoption tends to lower offshoring, both at the industry and the commuting zone level. These authors do not report evidence of whether there is a difference between offshoring in developed or developing countries. Reassuring the hypothesis of our paper, their results reveal that commuting zones that are more exposed to offshoring experience a relatively smaller negative effect on employment as a consequence of automation. This should be the case if automation by robots is reshoring some of the previously offshored activities.

3. Data Sources and Empirical Strategy

3.1. Data

We study bilateral imports of six developed countries sourced from 167 less developed countries, for the period 1995-2018. We chose France, Den-

[16] Wang (2020) finds that robot adoption in manufacturing firms in the US reduces employment and increases total firm imports (the paper does not differentiate between imports from developed or developing countries).

mark, the United States, the United Kingdom, Japan, and the Netherlands, because they are high-income countries[17] with ICT information at the aggregate and sector level. Additionally, the set of countries used for the instrumental variable approach is Finland, Italy, Sweden, and Norway.

3.1.1. Imports sourced from developing countries

We use trade data (imports and exports) from the Atlas of Economic Complexity Database (2019), which reports trade at the product level defined at 4-digits "Harmonized System" revision 1992 classification (HS92). We match this with US sectors defined at 4-digit North American Industry Classification System rev. 2007 (NAICS07).

For this, we use the crosswalk in Pierce and Schott (2012) for HS07 - NAICS07. We use the variables available in this database to create the share of imports and exports (by HS07) and leave the HS code with the highest share. Doing this we end up with 1221 unique NAICS-HS codes (where every NAICS has one or more HS associated). We merge this with crosswalk information available from the Unstat for HS07- HS92. We use this last classification to merge our trade data. To have a balanced panel, we complete the data with zero trade values.

We end up with 88 sectors defined at 4 digits NAICS classification and 167 developing trade partners for the period spanning from 1995 to 2018.[18]

[17]They were in the "high income" category of the World Bank in the year 2000.
[18]We only include developing partners with at least 1000 sector-bilateral observations.

We match industry-level trade data with the sector's occupation employment composition at the USA national-industry level from the Occupational Employment and Wage Statistics (OES) Survey - Bureau of Labor Statistics-[19].

3.1.2. New Technology Capital

We follow Acemoglu and Restrepo (2020b) to construct our adjusted level of penetration of ICT and software capital (a stock index). We divide sector ICT stock by the initial employment adjusted by the production growth[20]:

$$APICT_{s,c,t} = \frac{ICT_{s,c,t}}{EMP_{s,c,to}Y_{s,c,t}/Y_{s,c,to}} \tag{1}$$

where ICT is the Net Capital Stock of ICT, software, and Databases (Volume, USD 2015), EMP is sector employment, and Y is sector gross production (Volumen, USD 2015)[21] from STAN structural indicators (iSTAN) 2022 ed. from the OECD statistics, which is under the ISIC Rev.4 classification (2022a). Importantly, to avoid double counting we erased some observations[22]. We work with this variable in logarithm and create the respective

[19]This database contains information for NAICS 2007, SOC 2000, total employment and mean/median hourly/annual wage. We merge this with all of our indices and collapse them at the NAICS level (using as weights total employment).

[20]We estimate a fixed effect model in levels. Therefore our identification comes from the difference of APICT over time. Without loss of generality, we can think of our identification variability as: $APICT_{s,c,t} - APICT_{s,c,to} \approx \frac{ICT_{s,c,t}-ICT_{s,c,to}}{EMP_{s,c,to}} - \frac{Y_{s,c,t}-Y_{s,c,to}}{Y_{s,c,to}} \frac{ICT_{s,c,to}}{EMP_{s,c,to}}$.

[21]For the United Kingdom Gross Production is replaced with value-added because of data availability. Also, for this part, we do not consider Sweden (very few observations for the relevant variables).

[22]This is because there are countries that do not have some particular sector while others do (e.g. sector D16T18 would appear multiple times for Denmark because it has data at the aggregated and disaggregated level).

instrument following Equation 4.

For robustness, we construct a similar index for total capital (Net Capital Stock, Volume in USD 2015, $APK_{s,c,t}$) and robot using the International Federation of Robotics (IFR) data ($APRob_{s,c,t}$). According to this institution,[23] 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".

We work with IFR data for the operational stock of robots available from 1993 to 2016. We use a particular version of the ISIC Rev.4 industry classification (from now on ISIC_IFR). We apply some specific adjustments to this industry codes[24] and to the robot stock data. We create two weights as the share of robot stock (for every year and 2016 in particular), in terms of total stock discounting the unspecified sector data. With this, we create two measures: i) Stock of Robots adjusted for unspecified data using each year's weight and ii) Stock of Robots adjusted for unspecified data using 2016 weights. The mean of these two measures is our final stock of robot variable.

We leave our robot stock variables in terms of total employment at the industry level for 2000, using the number of persons engaged from STAN structural indicators (iSTAN) 2022 ed. from the OECD statistics, which is under the ISIC Rev.4 classification. Lastly, we create our instrument for

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

[24]e.g. replace industry C_271, C_275, and C_279 with C_27, or replace with missing values the cases of Mexico and Canada before 2010, information that appears for "North America" as a whole before that year (among other similar changes).

these variables (in logs) as described in Equation 4.

From 1995 to 2018, the (mean) annual growth rate for ICT capital per hour worked for the six developed countries under analysis is close to 9.6%, four times higher than the same measure for Total capital deepening (2.4%) during the same period (See Figure 2). These statistics emphasize the notable uptake of new technologies by developed economies in recent decades.

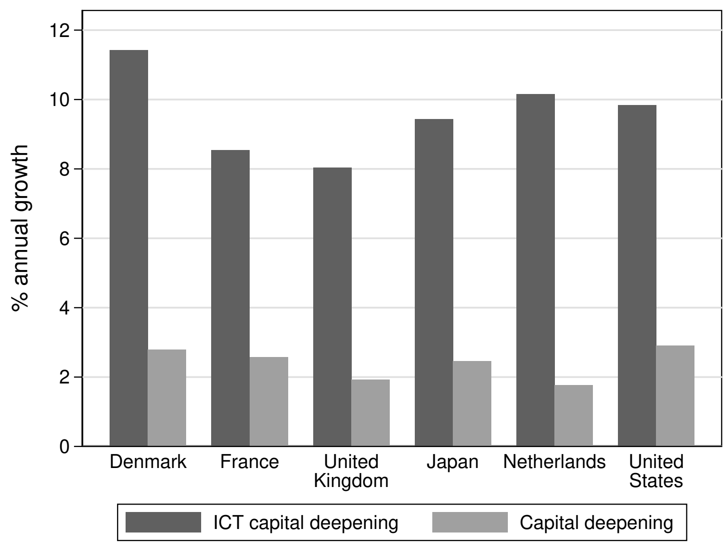

Figure 2: Mean Annual growth rate - ICT Capital and Capital in developed countries

Source: Own calculations based on OECD (2022b) data. Note: Annual growth for ICT capital deepening and Capital deepening (i.e. both measures in terms of total hours worked) in the USA between 1995 and 2018.

Lastly, it is important to mention that we use our ICT and robot stock measure as weighted means. To create the weights we used the following auxiliary databases: i) **BLS-OES NAICS employment:** data from the U.S. Bureau of Labor Statistics (BLS, Occupational Employment and

Wage Statistics, OES). We work with total employment at the industry level (NAICS07 at 4-digits) and aggregated level, and ii) **OECD ISIC Rev.4 employment:** data from the OECD. We work with the number of persons engaged (total employment, in thousands) only for the USA in 2007 at the industry level (ISIC Rev.4) and aggregated level. We use the crosswalk provided by the United Nations (Unstat) for ISIC Rev.4 and NAICS 2007[25] to merge both databases.

We end up with the ISIC Rev.4 and NAICS codes, and total employment at the industry and aggregated level (associated with each code separately). With this database (from now **original weight database**), we create the following measures:

$$Share\_emp\_ISIC = \frac{Emp\_ISIC}{Ag\_Emp\_ISIC}$$

$$Share\_emp\_NAICS = \frac{Emp\_NAICS}{Ag\_Emp\_NAICS}$$

$$Aux\_weight = \frac{Share\_emp\_ISIC * Share\_emp\_NAICS}{aux\_share\_ISIC}$$

Where aux_share_ISIC is equal to the sum of $Share\_emp\_NAICS$ by

[25] Initially, we worked with 1768 unique ISIC-NAICS code pairs. We add 13 additional codes, associated with the crosswalk for the following NAICS: 516100, 517300, 517500, and 518100. We also changed 9 ISIC codes that are at a higher level of disaggregation than needed in comparison with the ISIC's that appear in the ICT database used (e.g. the codes D05 and D06 are changed to D05T06). After these specific adjustments, we end up with 519 unique ISIC-NAICS codes

ISIC code. Then, we calculate the sum of Aux_weight by NAICS code (which we denominated $Aux\_weights\_NAICS$). With all these, we generate the following weight measure (use later):

$$Weight_1 = \frac{Aux\_weight}{aux\_weights\_NAICS}$$

Using the **original weight database**, we add a variable similar to the ISIC Rev.4 classification (from Unstat) but that is compatible with the ISIC codes in the IFR database (e.g. D01, D02, and D03 are equivalent to code "A"). We collapse the data by NAICS and ISIC_IFR codes and follow the same procedure as before, creating new weights based on this ISIC_IFR code. We add the countries (the six developed plus the four use in our IV strategy) and years. Lastly, we include the stock of robots (and instruments) information and create the weighted mean by industry (NAICS).

Additionally, we use the **original weight database** with the variable previously created ($weight_1$) and added a variable similar to the ISIC Rev.4 classification (from Unstat) but that is compatible with the ISIC codes in the ICT OECD database. We collapse $weight_1$, using as analytic weight the total employment at the industry level for the NAICS 2007. We merge this with the original $weight_1$ database to complete the information for some industries. We add the countries (the six developed plus the four used in our IV strategy) and years. Lastly, we include the ICT (and instruments) information and create the weighted mean by industry (NAICS).

3.1.3. Computerization and offshoring

Autor et al. (2003) (ALM) 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) broaden 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 method to classify 748 occupations according to the number of routine and non-routine tasks performed in 2000. 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.

We use occupation-task data provided by Acemoglu and Autor (2011) for the USA to construct our routine task/automation measure at the occupation level as follows:[26]

$$ROUT_o^{ALM} = \sum_{\tau \in \, routine} T_\tau^o - \sum_{\substack{\tau \in \, Non \\ routine}} T_\tau^o \qquad (2)$$

[26]Data available at "`https://economics.mit.edu/people/faculty/david-h-autor`". O*NET task measures used in that paper are composite measures of O*NET Work Activities and Work Context Importance scales.

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 ($ROUT_o^{ALM}$) signifies a proxy for the probability that occupation o is at risk of computerization. For each sector, we computed the employment weighted average of $ROUT_o^{ALM}$.[27] This is our main measure of sector j share of employment at risk of automation ($ROUT_j = \sum_o \frac{Emp_{o,j}}{Emp_j} ROUT_o^{ALM}$). We assume that the type of tasks contained across occupations is similar between the United States and the rest of the developed economies under analysis.

For robustness, we constructed an alternative proxy for computerization occupation risk [28].Frey and Osborne (2017) used an econometric method to assign the risk of automation to 702 occupations defined at the three- to six-digit level of the Occupational Employment Statistics (OES) 2010 Bureau of Labor Statistics definition (BLS). We merged 698 of these occupations with the OES employment dataset, and we extended the number of occupations to 788.[29] For each sector j, we computed the employment weighted average RISK Probability ($RISK_j$).

Additionally, we borrow Acemoglu and Autor (2011) offshorability index

[27]We use employment at occupation and sector level, defined at 4 digit NAICS rev2007, from the "Occupational Employment and Wage Statistics" 2007.

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

[29]We follow Micco (2019) to fulfill the 90 occupation index.

based on O*NET task measures and the work of Firpo et al. (2011) and, primarily, Blinder and Krueger (2013). It is similar in structure to what we described previously for our Routine Task Index ($PROB_j$). It considers seven O*NET scales (normalized)[30] and sector occupation employment data from the BLS 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, we computed the employment weighted average to obtain our measure of sector j share of employment at risk of offshorability (OFF_j).

We employ a binary variable for sector offshorability to enhance the clarity of result interpretation ($DOFF_j$) when we include at the same time our routine task index and the offshorability index. Our sector Binary Offshorability Index functions as a dummy variable, taking the value of one when the sector-level average of the occupation offshorability index by Blinder and Krueger (2013), weighted by employment (OFF_j), surpasses the median within our dataset of 88 sectors.

3.1.4. Other variables

For comparability, we construct a sector-level replaceability index a la Graetz and Michaels (2018b). These authors use data from IFR on robot

[30] 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.

applications and the U.S. Census Occupational Classifications. The IFR distinguishes between different applications of robots, including (among others) welding, painting, and assembling (IFR, 2012). They take the 2000 Census three-digit occupational classification and assign a replaceability value of 1 to an occupation if its title corresponds to at least one of the IFR application categories and 0 otherwise. We take their replaceability index at the occupation level from Graetz and Michaels (2018a), and we compute its sector average, weighted by OES-BLS employment in 2007 (REP_j). Finally, using the OES-BLS database 2007, we compute the USA sector average (ln) hourly wage ($lnWage_j$).

3.2. Indices: crosswalks and merging process

We use the SOC 2000 classification to merge all the indices previously described: i) the Frey and Osborne (2017) index is at the level of the census occupational code (Standard Occupational Classification, SOC) 2010. We use a crosswalk for SOC2000 and SOC2010 from the BLS to merge the data and end up with the FO index at the SOC 2000 classification (6 digits). [31] ii) the replaceability index from Graetz and Michaels (2018b) is at the SOC 1990 level. We use the American Community Survey (ACS) for 2000 to obtain a crosswalk for SOC1990 and SOC2000. We end up with a weighted (by the available person weights in the database) average of the replaceability index,

[31] We also create a dummy equal to 1 if the computerization risk by FO is equal to or higher than 0.70.

at the SOC 2000 classification. iii) the routine tasks and offshoring measures are originally at SOC2000 and come directly from the MIT Economics webpage for the paper of Acemoglu and Autor (2011). We merge this data with the replaceability index. We collapse the task measures by SOC2000 (using the weight available in the original database). Then, the task measures are standardize and use to construct ROUT in the way described in Equation 2. Lastly, we include the FO index.

Finally, as we need this information at the industry level, we used the U.S. Bureau of Labor Statistics (Occupational Employment and Wage Statistics, OES) database, which contains information for NAICS 2007, SOC 2000, total employment and mean/median hourly/annual wage. We merge this with our indices and collapse them at the NAIC level (using as weights total employment).

3.2.1. Summary Statistics and Pairwise Correlations

Table 1 Panel A reports the summary statistics of bilateral imports at the sector level in log ($Import(ln)$), our proxies for the risk of computerization/automation ($ROUT_j$ & $RISK_j$), offshorability (OFF_j), replaceability (REP_j) and the adjusted level of penetration of ICT ($ln(APICT)$) and total capital in log ($ln(APK)$). All variables, but imports, are normalized to have a standard deviation equal to one, and also zero mean in the case of our risk of automation and offshorability indices. We include the Replaceability Index, used in previous studies, to see if it captures the same type of tasks that our computerization/automation indices.

Table 1: Descriptive Statistics

PANEL A: Summary Statistics (Bilateral-sector-year data)

	Obs.	Mean	Std.Dev.	Min.	Max.
Import (ln)	917,676	12.62	3.39	1.39	25.35
$ROUT$	917,676	0.0	1.0	-2.9	2.48
$RISK$	917,676	0.0	1.0	-3.82	1.45
OFF	917,676	0.0	1.0	-3.07	2.71
$APICT$ (ln)	879,502	1.69	1.0	-1.84	5.58
APK (ln)	894,525	5.5	1.0	1.85	10.23
REP	917,676	0.0	1.0	-2.66	2.03

PANEL B: Pairwise correlation (Sector data)

	$ROUT$	$RISK$	OFF	REP	$(ln)Wage$
$ROUT$	1.00				
$RISK$	0.80	1.00			
OFF	0.29	-0.04	1.00		
REP	0.44	0.47	-0.06	1.00	
$(ln)Wage$	-0.86	-0.86	-0.24	-0.33	1.00

Note: $Import(ln)$ Log imports of products from 88 sectors in developed countries that originate from less developed countries. $ROUT$ Sector Routine Task Index a la Autor et al. (2003), $RISK$ Sector Automation Risk Index a la Frey and Osborne (2017), OFF Sector Offshorability Index a la Blinder and Krueger (2013), REP Sector Replaceability Index a la Graetz and Michaels (2018b), $APICT$ and APK Developed country-sector Adjusted level of Penetration of ICT and total capital, and REP Sector Replaceability Index a la Graetz and Michaels (2018b). $Wage(ln)$ Sector log wages in the USA in 2007.

Table 1 PANEL B reports pairwise correlations of previous measures. We also include the sector average (ln) hourly wage in the USA in 2007 ($lnWage_j$). The correlation between the Routine Task Index a la Autor and Handel (2013) and Risk of Automation a la Frey and Osborne (2017) is high ($corr(ROUT_j, RISK_j) = 0.8$). This high correlation reassures that both indices capture the same features of occupations. There is a strong negative correlation between the level of the sector Routine Task Index and higher wages ($corr(ROUT_j, lnWage_j) = 0.9$). The same is true for the RISK of automation index. There is no correlation between Offshoreability (OFF_j) and computerization/automation indexes. The correlation is 0.29 with $ROUT_j$ but -0.04 with $RISK_j$. The correlation between offshorability and wages is negative, although small ($corr(OFF_j, lnWage_j) = -0.24$).

The correlation between the Replaceability Index à la Graetz and Michaels (2018b) and the Routine Index is only 0.44, and even lower, in absolute value, with sector (ln) wage ($corr(REP_j, lnWage_j) = -0.33$). The Replaceability Index, used in previous studies, captures different features of occupations (than the ROUT and the RISK Index) that are less negatively correlated with wages. Hence, robot penetration, which undertakes tasks measured by the replaceability index, should have a lower effect on bilateral imports from countries that relied on low wages as their comparative advantage.

To gain an initial understanding of the relationship between sector bilateral imports ($lnImport$), and the Routine Task ($ROUT_j$) and Offshorability (OFF_j) indices, we regress $lnImport_{yjx}$ on both indices interacted by year dummies. We also include importer and exporter year dummies and sector bilateral import dummies. Figure 3 reports the year-by-year estimated coefficients for $ROUT_j$ and OFF_j.

The estimated coefficients for the Routine Index suggest a continuous decline in imports within sectors characterized by routine tasks relative to other sectors. The annual growth rate of imports in a sector with one standard deviation higher Routine Task Index is 1.2 percentage points lower than the

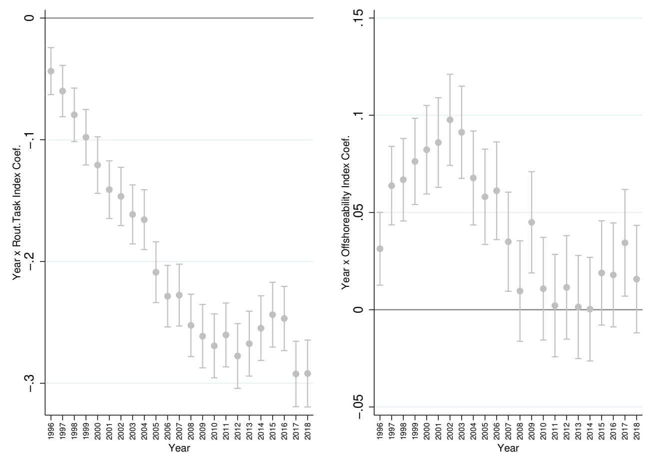

Figure 3: Estimated Coefficients of Routine Task and Offshoring Indices by year

Note: log of imports regress on Routine Task ($ROUT_j$) and Offshorability (OFF_j) indices both interacted by year dummies. Indices are normalized to have mean zero and standard deviation one. Fixed effects by importer and exporter-year, and bilateral-sector. 90 percent confidence interval.

average imports growth from 1995-2018. The negative trend is steeper until 2010. Between 2010 and 2016, the relative imports remained flat, but the negative trend reappeared in 2017.

The findings regarding the Offshorability Index reveal an increase in imports within sectors associated with offshorable occupations during the initial seven years of the sample period. However, this trend reversed between 2003 and 2011, and then it remained stable. These findings are consistent with Antràs (2020), who suggests that trade experienced growth in the 1990s due to the profitability of fragmenting production processes. However, in recent decades, technological advancements have facilitated task automation, leading to reduced labor costs and the substitution of offshoring for certain activities.

3.3. Econometric Model

We exploit cross-sector variation in the share of employment in occupations prone to computerization/automation ($ROUT_j$) to identify the effect of the surge of ICT-software investment across sectors in developed countries ($ln(APICT_{yjt})$) on the export composition of less developing countries.

$$\begin{aligned} ln(Imp_{yjxt}) &= \delta_1 ROUT_j \; ln(APICT_{yjt}) + \delta_2 ln(APICT_{yjt}) \\ &+ \delta_3 DOFF_j \; ROUT_j \; ln(APICT_{yjt}) + \delta_4 DOFF_j \; ln(APICT_{yjt}) \\ &+ \alpha_{xt} + \alpha_{yt} + \alpha_{yjx} + \varepsilon_{yjxt} \end{aligned} \tag{3}$$

Where y corresponds to one of the six developed countries (importers), x one of the developing countries (exporters), j one of the 88 sectors, and t the year. The dependent variable is the logarithm of imports ($ln(Imp_{yjxt})$). The independent variable of interest is the interaction between the Routine Task Index ($ROUT_j$) and the logarithm of our ICT penetration index at the developed country-industry level ($ln(APICT_{yjt})$). We also consider an interaction term with a Binary Offshorability Index ($DOFF_j$) to account for an offshoring or reshoring process.

We include a set of fixed effects, α_{yt} to capture aggregate demand shocks at the importer-country level, α_{xt} for aggregate supply shocks, and bilateral trade-sector dummies (α_{yjx}) to control for the initial bilateral sector import level. Errors are clustered at the bilateral sector level.

As we already mentioned, our adjusted level of penetration of ICT *(ln(APICT))* may suffer from measurement error and endogeneity. Following Acemoglu and Restrepo (2020a), we instrument the sector-country adjusted penetration of ICT capital ($ln(APICT_{yjt})$) using the simple average of the analogous measure constructed from 9 different developed countries:[32]

$$IVln(APICT_{yjt}) = \frac{1}{9}\sum_{z\neq y} ln(APICT_{zjt}) \tag{4}$$

For robustness, we do additional exercises. First, we estimate Equation 3 using the Poisson Pseudo Maximum Likelihood estimation (PPML) to account for the zero trade data. Second, we evaluate the effects when considering only the bilateral trade between the six developed economies. Third, we replace ICT with total capital penetration to check we are capturing a special feature of ICT capital. In these last two exercises, we expect effects of lower magnitude/opposite sign or with an insignificant impact. Fourth, to compare our findings with the previous literature, we include the sector-specific robot penetration and the Replaceability Index. Finally, we redo the models excluding countries from the sample (USA, China, and Mexico) and

[32]To compute the instrumental variable, we use Finland, Italy, Sweden, and Norway, in addition to the six developed countries in our sample. The simple average does not take into account the country for which we construct the measure (therefore it is 9 countries and not 10). The additional four countries considered to construct the IV have more missing data than the six we consider in our sample.

we use the RISK Index à la Frey and Osborne (2017) instead of the Routine Task Index.

4. Main Results

4.1. Effects of Computerization/automation on Trade

Table 2 focuses only on the direct effect of computerization/automation, proxy with the Routine Task Index on trade. We do not include the interaction effect of the Offshorability times ICT penetration, but we do include the Offshorability Index times year dummies. All models include importer and exporter time fixed effects and bilateral-product fixed effects. Column [1] reports the estimated parameters using OLS. The interaction effect between the Routine Task Index and the sector-adjusted penetration of ICT ($ROUT_j \times lnAPICT_{yjt}$) is negative and highly significant. The estimated coefficient (-0.152) implies that one standard deviation increase in ICT penetration reduces imports by 15 percent in a sector with one standard deviation higher $ROUT_j$ relative to the average sector during the whole period 1995-2018. On average, imports increased 0.7 percent less per year. The main effect of ICT penetration is negative and significant, although negligible. Even though we demean $ROUT_j$, and therefore this coefficient should capture the mean effect of sector ICT penetration on imports, the identification assumption is much stronger to imply this causal effect.

Column [2] uses the Poisson Pseudo Maximum Likelihood estimation (PPML) to account for the zero import data. The number of observations almost doubled, but the estimated coefficient of interest, $ROUT \times ln(APICT)$, remains almost the same and highly significant.

To control for the potential endogeneity of ICT penetration, in column [3] we estimate the model using instrumental variables defined in Equation (4). The interaction term is still negative and highly significant, and larger in absolute value than the one in column [1]. This result suggests that the reverse causality is weak and measurement errors downward bias the coefficient. The Cragg-Donald Wald F statistic rejects the null hypothesis that the instrumented variable is weakly identified. We redo the same econometric model using the RISK of Automation Index a la Frey and Osborne (2017) instead of the Routine Task Index. The interaction coefficient between RISK and ICT penetration, reported in Table 4 (robustness) is negative and highly significant as in Column [3].

The Armington elasticity is a key parameter in quantitative trade models, as it determines the level of substitutability between domestic and imported varieties of a good. A higher Armington elasticity means that a given product is more substitutable, or less differentiated, and so we should expect a larger effect on import flows of this product, for a given ICT penetration, than in the case of a lower value. There is a vast empirical literature that studies how the Armington elasticity varies across products used for final consumption and intermediate inputs. [33] Although the evidence is not conclusive, most

[33] We thank an anonymous referee for raising this issue.

empirical literature found that intermediate goods have higher Armington elasticities than final goods (see Saito (2004), Lopez and Pagoulatos (2002), Ceglowski (2014), and Leigh et al. (2015).).

We use the USA Input-Output table for the year 2000 to classify sectors into intermediate input sectors and final product sectors. [34] Columns [4] and [5] redo the econometric model in column [3] for final product and intermediate input sectors, respectively. As we should expect from the previous discussion, the estimated interaction coefficient between ROUT and ICT penetration is larger for intermediate input (-0.271) than for final products (-0.218), although the difference is small relative to their estimated standard errors.

In Column [6], using instrumental variables, we now consider trade only between our six developed countries (i.e. the exporter country considered here is also one of our six developed countries). This is to check that our previous results capture the fact that developing countries that specialize in goods produced by low-wage tasks occupations are the ones losing their comparative advantage (i.e. this does not happen for developed countries). In this specification, contrary to previous exercises, exporter countries also have a high level of ICT penetration. We control for it ($ROUT \times ln(APICT)Exporter$). As we should expect, our coefficient of interest $ROUT\times$

[34]We use the "Use of Commodities by Industries" table from the BEA. For each sector we compute the share used as intermediate goods, and we classified sectors above and below the median value.

$ln(APICT)$ is half the size of the coefficient for exports from less developed countries (column [3]).

To test whether we are capturing the impact of new technology and no investment in capital, in Column [7] we redo the model in Column [3] but we use total capital instead of ICT penetration. We do not find a negative coefficient for total capital penetration times Routine Task Index. The coefficient is positive, suggesting that in this case, where the productivity does not reduce the labor costs due to automation, the productivity/scale effect dominates.

To compare our findings with the literature that focuses on robot penetration, the last two columns include the sector-specific robot penetration times the Replaceability Index. In Column [8], we used OLS. Notably, our coefficient of interest remains unchanged ($ROUT \times ln(APICT)$), and the interaction term of the Replaceability Index and sector robot penetration is positive and significant ($REP \times ln(APRobots)$), consistent with the findings of Artuc et al. (2020). In Column [9], we employed the IV approach. The relationship between $ROUT$ and ICT remains negative and highly significant. The interaction term of the Replaceability Index and robot penetration is still positive but no longer statistically significant.

From Table 4 we know that robot penetration and investment in computers, communication, and software replace different tasks in different occupations with different levels of wages. Results from the IV analysis in Column [9] indicate that the penetration of ICT in developed countries has changed the relative exports of less developed economies during our analysis periods. We do not observe a similar effect with the penetration of robots. As previously stated, this disparity could stem from the ongoing lower investment in robots compared to ICT, as well as the fact that the tasks replaced by robots are less centralized in low-wage occupations.

4.2. Effects of Computerization/automation and offshoring on Trade

Table 3, instead of controlling by offshoring times year dummies, controls the direct impact of offshoring on trade using an Offshorability dummy times ICT capital penetration ($DOFF \times ln(APICT)$). In all models, we instrument ICT capital penetration and we include importer and exporter year, and bilateral sector fixed effects. Column [1] reports the estimated IV parameter for $ROUT$ times ICT penetration when we control for $DOFF \times ln(APICT)$. The coefficient of $ROUT \times ln(APICT)$ is negative and highly significant, although larger, in absolute value, than when we do not include the Offshorability dummy times ICT penetration. The latter coefficient is negative but not statistically significant at standard levels. This is the average effect during the whole period, and from Figure 3 we know there is a positive relationship between offshorability and imports until 2001, and then this relationship becomes negative.

To account for this inverse U relation, Column [2] includes a second sector Offshorability dummy times ICT penetration for the Post-2001 period. The estimated coefficient for $ROUT \times ln(APICT)$ remains negative and highly

Table 2: Imports and Sector Routine Task Index

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	$(ln)Import$	(sum) import_value	$(ln)Import$	$(ln)Import$	$(ln)Import$	$(ln)Import$	$(ln)Import$	$(ln)Import$	$(ln)Import$
$ROUT \times ln(APICT)Exporter$						-0.0991**			
						(0.0478)			
$ln(APICT)Exporter$						0.161*			
						(0.0883)			
$ROUT \times ln(APICT)$	-0.152***	-0.145***	-0.267***	-0.218***	-0.271***	-0.132***		-0.159***	-0.398***
	(0.00888)	(0.0255)	(0.0370)	(0.0494)	(0.0511)	(0.0408)		(0.00936)	(0.0723)
$ln(APICT)$	-0.0577***	0.0414	-1.124***	-1.009***	-1.245***	0.178**		-0.0500***	-0.835***
	(0.0140)	(0.0376)	(0.0916)	(0.0892)	(0.326)	(0.0832)		(0.0147)	(0.119)
$ROUT \times ln(APK)$							0.201***		
							(0.0481)		
$ln(APK)$							-0.248***		
							(0.0902)		
$REP \times ln(APRobots)$								0.0257***	0.0641
								(0.00859)	(0.0516)
$ln(APRobots)$								0.0914***	0.0775
								(0.0113)	(0.0588)
Observations	872,323	1,530,775	872,323	506,442	365,880	55,822	887,283	774,134	774,134
Sample	All	All	All	Final Dda.	Input	Dev.Cty	All	All	All
Method	OLS	Poisson	IV	IV	IV	IV	IV	OLS	IV
CD Wald F			7316	4534	754.6	2098	10900		1116

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Robust Standard errors cluster by bilateral-sector in parenthesis. Significant level *** p<0,01, ** p<0,05, * p<0,1 Note: $ROUT$ is the Routine Task Index a la Autor et al. (2003). $ln(APICT)$, $ln(APK)$, and $ln(APK)$ are the sector-adjusted ICT capital, total capital, and robot penetration, respectively. REP is the Replaceability Index a la Graetz and Michaels (2018b). $ROUT$ and REP have a mean of 0 and a standard deviation of 1. All models include fixed effects by importer country-year, exporting country-year, and bilateral-sector.

significant. As we should expect from Figure 3 and in line with Antràs (2020), the first Offshorability interaction term for the whole period is positive and significant, and the second for the Post-2001 period is negative and significant. One standard deviation increase in ICT penetration increases relative imports by 20% during the initial 7 years in our sample, but this effect is attenuated by half Post-2001.

Column [3] includes a triple interaction term between the Routine Index, the Offshorability, and ICT penetration. The estimated coefficient is negative but very close to 0 and not statistically significant. In Column [4] we redo the same model and we include a set of year dummies times the Offshorability Index. The triple interaction term remains not statistically different from 0.

Previous results show that as the ICT capital deepening process takes place in our sample of developed countries, the automation of routine human tasks in the production of mainly low-skilled labor intensive products, in which developing countries have a comparative advantage, is reducing developed countries imports from developing economies in theses products. Ceteris paribus, the ICT capital deepening process might shrink overall bilateral trade between developed and developing countries, mainly in terms of developed countries' imports.

To provide evidence about overall imports, in Section 7 (Appendix A), Figure 7 reports the evolution of imports from developing countries, adjusted

Table 3: Imports and Sector Routine Task and Offshore Index

VARIABLES	(1) (ln)import	(2) (ln)import	(3) (ln)import	(4) (ln)import
$ROUT \times ln(APICT)$	-0.381***	-0.416***	-0.386***	-0.286***
	(0.0254)	(0.0468)	(0.0612)	(0.0666)
$ln(APICT)$	-0.902***	-1.279***	-1.312***	-2.196***
	(0.0648)	(0.231)	(0.224)	(0.376)
$DOFF \times ln(APICT)$	-0.0115	0.221***	0.238***	0.689***
	(0.0367)	(0.0512)	(0.0536)	(0.133)
$DOFF \times ln(APICT)$		-0.102***	-0.110***	-0.207***
$Expost$ 2001		(0.0253)	(0.0243)	(0.0458)
$ln(APICT)$		0.00103	0.00327	-0.0301
$Expost$ 2001		(0.0551)	(0.0561)	(0.0641)
$ROUT \times DOFF \times ln(APICT)$			-0.0439	-0.0706
			(0.0511)	(0.0587)
Observations	872,323	872,323	872,323	872,323
Method	IV	IV	IV	IV
Sample	ALL	ALL	ALL	ALL
CD Wald F	8580	380	345.2	199.9

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Robust Standard errors cluster by bilateral-sector in parenthesis. Significant level *** p<0,01, ** p<0,05, * p<0,1 Note: $ROUT$ is the Routine Task Index a la Autor et al. (2003). $ln(APICT)$ is the sector-adjusted ICT capital. $DOFF$ is the sector binary Offshorability Index a la Graetz and Michaels (2018b). $ROUT$ has mean 0 and a standard deviation of 1. $Post2001$ is a dummy variable equal to one post the year 2001. All models include fixed effects by importer country-year, exporting country-year, and bilateral-sector.

by GDP,[35] for Denmark, France, Great Britain, Japan, the Netherlands, and the United States during our sample period. As suggested by the previous discussion, each country exhibits a downward trend in the aggregate share of imports from developing countries (adjusted by GDP). It is important to note that our econometrics strategy, grounded in the methodology of Rajan and Zingales (1998), enables us to estimate a causal effect solely on the relative evolution of sectoral imports.

5. Robustness

In Table 4 we redo Column [3] in Table 3 and Column [2] in Table 2 excluding some countries from the sample. First, we exclude the USA as an importer country, second, we exclude China, and third Mexico. In all cases the same conclusions hold. In the last three columns in Table 4, we use the computerization/automation RISK Index a la Frey and Osborne (2017) instead of the Routine Index. We find that the interaction coefficient between the RISK Index and ICT penetration is negative and highly significant. When we include the interaction term between the Offshorability dummy and ICT penetration allowing for different effects pre and post-2001, our main variable of interest, the RISK Index times ICT penetration, is still negative and highly significant. Although results show that the Offshorability dummy times ICT penetration becomes more negative in the post-2001 period, the

[35] We compute, for each developed country, the share of imports from developing countries divided by the GDP share of those same developing countries.

coefficients are not statistically significant. Finally, we include in the previous model the triple interaction between the RISK Index, the Offshorability dummy, and ICT penetration. The Offshorability Index times ICT penetration is positive in the period pre-2001, it becomes negative and statistically significant after 2001, and the triple interaction term with the RISK index is negative. This last result is in line with the idea that in the last decades, previously offshoring tasks have been reshoring in the case in which they can be performed by new technology capital.

6. Conclusions

The notion of comparative advantage has long been a fundamental concept in understanding international trade. Traditionally, less developed countries have found their comparative advantage in sectors characterized by routine labor-intensive tasks, which were sustained by their competitive advantage in low wages. However, this landscape is rapidly transforming due to the advent of new technologies that are disrupting traditional production patterns.

In contrast to previous studies that primarily focus on robot penetration, our research delves into the effects of investment in computers, communication, and software on imports from developing countries in developed economies. We concentrate on sectors characterized by routine tasks, which, as identified by Autor and Handel (2013) are at risk of computerization. This key distinction adds significant value to our investigation. Notably, previous

Table 4: Robustness

VARIABLES	(1) ln(import)	(2) ln(import)	(3) ln(import)	(4) ln(import)	(5) ln(import)	(6) ln(import)	(7) ln(import)	(8) ln(import)	(9) ln(import)
$ROUT \times ln(APICT)$	-0.432***	-0.970***	-0.267***	-0.411***	-0.267***	-0.419***			
	(0.0504)	(0.185)	(0.0370)	(0.0466)	(0.0370)	(0.0472)			
$ln(APICT)$	-1.243***	-1.599***	-1.124***	-1.164***	-1.124***	-1.271***	-1.134***	-0.391***	-0.576***
	(0.0773)	(0.270)	(0.0916)	(0.232)	(0.0916)	(0.232)	(0.0922)	(0.148)	(0.125)
$DOFF \times ln(APICT)$		-0.131		0.195***		0.217***		-0.00690	0.0860
		(0.104)		(0.0510)		(0.0515)		(0.0472)	(0.0524)
$DOFF \times ln(APICT)$		-0.0816***		-0.0884***		-0.104***		-0.0275	-0.0566***
$Expost$ 2001		(0.0200)		(0.0255)		(0.0255)		(0.0213)	(0.0181)
$ln(APICT)$		-0.217*		0.0172		-0.00137		0.238***	0.241***
$Expost$ 2001		(0.119)		(0.0553)		(0.0556)		(0.0290)	(0.0297)
$RISK \times ln(APICT)$							-0.132***	-0.158***	-0.0602
							(0.0429)	(0.0330)	(0.0416)
$RISK \times DOFF$									-0.188***
$\times ln(APICT)$									(0.0620)
Observations	674,507	674,507	872,323	860,450	872,323	861,814	872,323	872,323	872,323
Method	IV	IV	IV	IV	IV	IV	IV	IV	IV
Sample	$\neq$ USA	$\neq$ USA	$\neq$ CHN	$\neq$ CHN	$\neq$ MEX	$\neq$ MEX	ALL	ALL	ALL
CD Wald F	11041	245.7	7316	364.3	7316	375.5	6026	861.5	898.9

Robust Standard errors cluster by bilateral-sector in parenthesis. Significant level *** p<0,01, ** p<0,05, * p<0,1 Note: $ROUT$ is the Routine Task Index a la Autor et al. (2003). $RISK$ is the Probability of Computerization/Automation a la Frey and Osborne (2017). $DOFF$ is the sector binary Offshorability Index a la Graetz and Michaels (2018b) . $ln(APICT)$ is the log sector adjusted ICT capital. $ROUT$ and $RISK$ have mean 0 and a standard deviation 1. $Post2001$ is a dummy variable equal to one post the year 2001. All models include fixed effects by importer country-year, exporting country-year and bilateral-sector. Columns [1], [3], [5] [7] also include the continuous Offshorability Index times year dummies ($OFF \times DYear$). In all models we instrument sector $ln(APICT)$.

literature reveals that investment in robots constitutes only a tiny fraction of total equipment investment over the past decade, accounting for less than one percent. Furthermore, we report evidence that there is a robust negative correlation between occupations associated with routine tasks and high wages, whereas this correlation is notably weaker for occupations that robots can potentially replace. These could explain why previous studies do not provide clear evidence of the relationship between robot penetrations in developed countries and imports sourced from less developed economies.

Our research reveals a significant decline in developed countries´ imports of products from sectors reliant on routine tasks, which are more susceptible to computerization/automation. This decline is especially pronounced in sectors where advanced information and communication technology adoption has been prevalent. One standard deviation increase in ICT penetration reduces the annual rate of growth of imports in a sector with one standard deviation higher index of routine tasks by 0.7-2.2 percentage points.

Sectors with a high index of offshorability, as proposed by Blinder and Krueger (2013), that have invested in ICT exhibit a high level of import sourced from developing countries until 2001. However, following Antràs (2020), during the 21st century, imports in these sectors started to decline.

In our paper, we investigate the association between sectors dominated by occupations involving routine tasks and sectors characterized by tasks susceptible to offshoring. We find a weak relationship between these two types of occupations. The simple correlation at the occupation level is nearly zero, and this translates to a close-to-zero correlation at the sector level. Consequently, while north-south trade is linked to the presence of routine tasks and offshorability tasks within sectors, the behavior of imports remains unaffected by the joint condition of these factors.

The labor-replacing technologies that are primarily affecting low-wage occupations, characterized by routine tasks, are changing the comparative advantages of developing economies. The adjustment process to this new situation may have an important welfare impact on developing countries. [36]

7. Appendix A: The Share of imports from developing countries

In the Appendix, we compute the evolution of imports from developing countries ($UDev$), adjusted by GDP, for the six developed countries j in our sample.

$$R^j_{UDev.} = \frac{Imp^j_{UDev.}}{Imp^j_{Total}} / \frac{GDP^j_{UDev.}}{GDP^j_{Partners}}$$

. where $Imp^j_{UDev.}$ and Imp^j_{Total} are the sum of country j imports from developing countries and total country j imports, respectively. $GDP^j_{Partners}$ is the sum of country "j" import partners.

Figure 7 presents R^j_{UDev} for Denmark (DNK), France (FRA), Great Britain

[36]Chen J and Trottner (2023) argues that the China-USA trade war could have a positive effect on Mexico in the long run but a reduction in welfare during the adjustment process. In the USA, the China Trade Shock, which had heterogeneous effects on the economy, had lasting and painful consequences on some labor markets (Autor et al. (2021) and Autor et al. (2014))

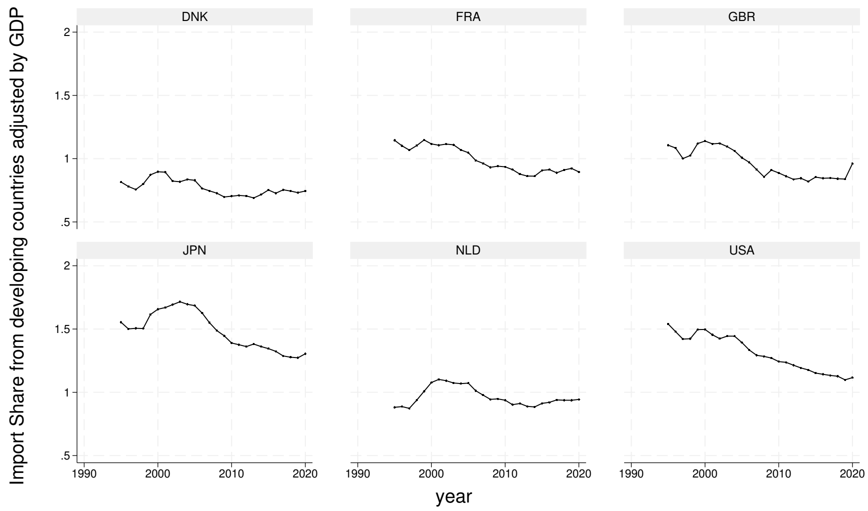

Figure 4: Import Share from Developing Countries Adjusted by GDP

Source: The Growth Lab at Harvard University and World Development Indicator World Bank.

(GBR), Japan (JPN), Netherlands (NLD) and the United States (USA). For each country, Figure 7 reports a downward trend for the share of imports from developing countries (adjusted by GDP).

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