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Have Robots Grounded the Flying Geese?

Evidence from Greenfield FDI in Manufacturing

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Abstract

For decades, manufacturers around the world have outsourced production to countries with lower labor costs. However, there is a concern that robotization in high-income countries will challenge this shifting international division of labor known as the "flying geese" paradigm. Greenfield foreign direct investment decisions constitute a forward-looking indicator of where production is expected, rather than trade flows that reflect past investment decisions. Exploiting differences across countries and industries, the intensity of robot use in high-income countries has a positive impact on foreign direct investment growth from high-income countries to low- and middle-income countries over 2004–15. Past a threshold, however, increased robotization in high-income countries has a negative impact on foreign direct investment growth. Only 3 percent of the sample exceeds the threshold level beyond which further automation results in negative foreign direct investment growth and is consistent with re-shoring. For another 25 percent of the sample, the impact of robotization on the growth of foreign direct investment is positive, but at a rate that is declining. So, although these are early warning signs, automation in high-income countries has resulted in growing foreign direct investment for more than two-thirds of the sample under consideration. Some geese may be slowing, but for now, most continue to fly.

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1. Introduction

During the last four decades, manufacturers all over the world have outsourced production to countries with lower labor costs. American, European, and Japanese firms moved a lot of their production to developing Asia and Latin America, first helping countries like Malaysia and Chile, then others like China and Mexico, and then others like Vietnam and Bangladesh. This shifting production of labor-intensive goods and tasks to countries with lower labor costs in a pattern that then reproduces itself among countries in the lower tiers is often described as the "flying geese" paradigm (Akamatsu 1962). There is widespread concern today that use of labor-saving technologies associated with Industry 4.0 — such as robotics, the Internet of Things, and 3-D printing — in established manufacturing centers may slow down opportunities for offshoring production to lower-cost locations and even lead to the active reshoring of production back to higher-wage locations.

There is an increasing amount of anecdotal evidence, which suggests that increased automation in high-income countries has already enabled some leading firms to re-shore historically labor-intensive manufacturing activities back to high-income economies. Foxconn, the world's largest contract electronics manufacturer, best known for manufacturing Apple's iPhone, has recently announced it will spend $40 million at a new factory in Pennsylvania, using advanced robots (Lewis 2014). Airtex Design Group is shifting part of its textile production from China back to the United States (*New York Times* 2013). And there is the most cited example of Adidas, which established "Speedfactories" in Ansbach, Germany, and Atlanta, to produce athletic footwear using computerized knitting, robotic cutting, and 3-D printing (*Assembly* 2012; Bloomberg 2012; *Economist* 2017a, 2017b; *Financial Times* 2016).

Adidas' recent announcement in November 2019 that it will close its "Speedfactories" in Germany and the United States may, on the one hand, assuage some of the fears the earlier headlines raised. On the other hand, the fact that these automated production lines will instead be moved to China and Vietnam where 90% of Adidas' suppliers are currently located may yet ground the 'flying geese'. This is not an isolated example. Foxconn—the Taiwanese firm known for producing Apple and Samsung products in China's Jiangsu province—recently replaced 60,000 factory workers with industrial robots (*South China Morning Post* 2016). In fact, China has installed more industrial robots than any other country and is rapidly automating to address declining wage competitiveness. This is important given that China's rising wages and production upgrading had created expectations of an en masse migration of light manufacturing activities to poorer economies with lower labor costs, such as those in Sub-Saharan Africa.

More systematic evidence on automation and offshoring is few and far between. Based on firm-level data for 3,313 manufacturing companies across seven European countries, Kinkel, Jager and Zanker (2015) find that firms using industrial robots in their manufacturing processes are less likely to offshore production activities outside Europe. Similarly, Artuc, Christiaensen, and Winkler (2019) show that an increase of one robot per 1,000 workers in the United States—about twice the increase observed between 2004–2014—lowers growth in exports per worker from Mexico to the United States by 6.7 percent. Artuc, Bastos and Rijkers (2019) show that a 10-percentage point increase in robot density in developed countries is associated with a 6.1 percentage point increase in their imports from less developed countries and a 11.8 percentage point increase in their exports to these countries, such that net imports from the South within the same sector decline by 5.7 percentage points.[2] Last, but not least, comparing growth in hearing aid trade – which is entirely 3D printed – with other similar products and controlling for a range of other relevant variables that might have changed during this period, Freund, Mulabdic and Ruta (2019) find that 3D printing increased trade by 58 percent over nearly a decade. They also indicate that there is no reversal in comparative advantage and early innovators in Europe, such as Denmark and Switzerland, remain the main export platforms.[3]

This paper contributes to this evidence base by analyzing the association between the intensity of robot use in high-income countries and offshoring as manifested in greenfield foreign direct investment flows from high-income countries to low- and middle-income countries. Unlike trade flows and other investments, which can be sticky and slow to change in response to other factors, these greenfield FDI data represent announcements and are therefore forward-looking. The intensity in use of robots has been steadily increasing in high-income countries over the last two decades, albeit differently across manufacturing industries. Among key GVC sectors, whereas transportation equipment and electronics have been steadily robotized since the 2000s, apparel remains relatively labor intensive. The rate of adoption across countries is also different, providing important sector-country-time variation. Based on country-sector panel data on FDI and industrial robots between 2004 and 2015, we find a 10 percent increase in the number of robots per 1,000 employees in HICs is associated with a 5.5 percent increase in the rate of change of the FDI stock from HICs to LMICs.

However, the relationship is not a linear one. Indeed, allowing for the effect to vary with the extent of automation finds there is a significant non-linear effect. The linear effect remains positive and significant. Past a threshold, however, the continued robotization is associated with a statistically significant decline in the rate of change in outbound FDI from HICs to LMICs. At the sample mean of robots per 1,000 workers (7.6), approximately one-third of the linear effect of automation is offset. At just over 24 robots per 1,000 employees is where the positive impact of automation is greatest. After that, continued robotization is associated with an increase in the growth of FDI but at a diminishing rate. However, less than 10 percent of the sample is above this threshold level of the intensity of robot use. The threshold level beyond which the marginal impact of the negative quadratic term outweighs the positive linear one to imply that further automation (578 robots per 1,000 employees) leads to an actual decline in outbound FDI from HICs to LMICs is not within the current range of data. Therefore, the increased intensity of robot use in HICs is associated with growth in outbound FDI from HICs to LMICs, which is increasing at an increasing rate for approximately 90 percent of the sample.

These results are robust to business cycle effects associated with the recent financial crisis, the exclusion of the transportation equipment sector, the inclusion of the stock of ICT capital per 1,000 workers engaged, and the inclusion and exclusion, respectively, of China as a source and destination country. Their robustness is also illustrated through an analysis of bilateral FDI flows where arm's length offshoring, market size effects, FDI restrictions and bilateral trade or investment agreements, respectively, were controlled by the inclusion of bilateral exports from

[2] The positive impact of robotization in the North on imports from the South is mainly driven by exchanges of parts and components.

[3] Beyond hearing aids, the authors find that 35 products that are increasingly being 3D printed have also experienced faster trade growth relative to other similar goods.

LMICs to HICs in the same industry in a given year, destination country-sector-time fixed effects as well as country pair-year and country pair-sector fixed effects.

These results remain qualitatively similar in a specification where industry-level trends in robot adoption in other countries with similar levels of income is used as an instrumental variable for a given country's robotization. However, the quantitative impacts are somewhat larger, and the threshold effects are reached at lower levels of automation. Now, about 28 percent of the sample is above the threshold level of robots per 1,000 employees beyond which additional automation results in a deceleration in the growth of FDI. Here, for the most automated country-sectors comprising about 3 percent of the sample, the negative quadratic effect more than offsets the positive linear term. This is indicative of automation leading to declines and not just decelerations of FDI. However, for more than two-thirds of the sample, automation has resulted in FDI increasing at an increasing rate.

This paper contributes to a broader literature, which analyzes how the diffusion of ICT technologies affects global production fragmentation and international trade patterns more generally by reducing coordination costs. Freund and Weinhold (2004) suggest that a 10-percentage point increase in the growth of web hosts for the average country in the sample contributed to about a 1 percentage point increase in annual export growth. Similarly, Osnago and Tan (2016) find that a 10 percent increase in an exporter's rate of Internet adoption led to a 1.9 percent increase in bilateral exports. Furthermore, Fort (2017) shows that the adoption of communication technology is associated with a 3.1 percentage point increase in the probability of production fragmentation based on a sample of U.S. firms. There is also evidence that ICT-enabled e-commerce platforms have boosted international trade by reducing the costs of matching buyers and sellers. For example, Lendle and Olarreaga (2017) find that the impact of distance on cross-border trade flows—across 61 countries and 40 product categories—is about 65 percent smaller for eBay transactions relative to total international trade.

This paper also adds to an emerging literature which seeks to identify the impact of industrial robots on a range of economic outcomes. Taking into account both the displacement and productivity effects of automation, Acemoglu and Restrepo 2017 find that the use of one more robot per 1,000 workers reduced the aggregate employment to population ratio by about 0.34 percentage points from 1990 to 2007 in the United States. For a sample of 17 advanced economies, Graetz and Michaels (2018) calculate that robot densification from 1993-2007 raised the annual growth of labor productivity by about 0.36 percentage point (compared to a mean growth of 2.4 percent). They also find significant negative implications of robots for the employment of low-skilled workers. Maloney and Molina (2016) look for evidence of polarization in labor markets in developing countries as a result of spreading automation and trade, but find limited evidence to date – although they flag automation in China as a key development still in relatively early stages that should be watched. Using administrative data on Mexican exports by municipality, sector and destination from 2004 to 2014, Artuc, Christiaensen, and Winkler (2019) show that higher exposure to U.S. automation did not affect overall wage or manufacturing employment. Yet, there were two counteracting forces; exposure to U.S. automation reduced manufacturing wage employment in areas where occupations were initially more susceptible to being automated, but exposure increased manufacturing wage employment in other areas.

The remainder of paper is as follows. Section 2 describes the data under consideration and provides descriptive statistics. Section 3 presents the empirical strategy to identify the impact of the intensity of robot use in HICs on greenfield FDI flows from HICs to LMICs. Section 4 concludes.

2. Data and Descriptive Statistics

The relationship between new automation technologies and GVCs is analyzed by combining data on the use of industrial robots from the International Federation of Robotics with data on greenfield FDI flows from the fDi Markets Database.

a) Foreign direct investment

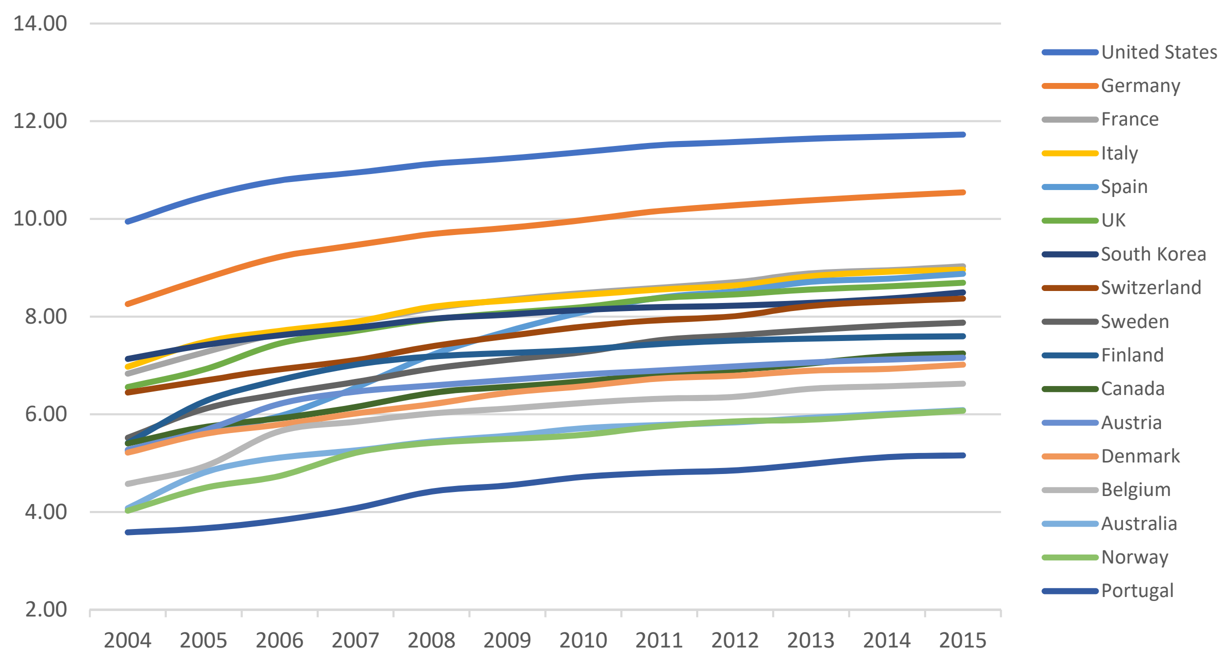
The data on foreign direct investment are taken from the fDi Markets Database, which is compiled by the Financial Times Group. fDi Intelligence has been tracking and verifying bilateral cross-border "greenfield" investment projects since 2003. The resulting fDi Markets Database provides annual information on the number and value of investment projects until 2015. Unlike other investments, which can be sticky and slow to change in response to other factors, these greenfield FDI data represent announcements and are therefore forward-looking. The database also enables the identification of tasks within industries, as it provides a business activity marker – for example, within apparel manufacturing, it distinguishes between manufacturing per se and design/retail services etc.

The literature distinguishes four types of FDI: (a) natural resource–seeking investment (focused on exploiting natural resources); (b) market-seeking investment (serving large domestic or regional markets); (c) strategic asset-seeking investment (driven by investor interest in acquiring strategic assets through mergers and acquisitions); and (d) efficiency-seeking investment. Of interest here is the last type of investment, which is typically export-oriented; leverages local factors of production to reduce costs; and involves the transfer of production and managerial know-how, access to distribution networks, and sources of finance. Greenfield FDI, by definition, excludes strategic asset-seeking FDI through mergers and acquisitions. Further, because these data go beyond country aggregates and consider differences at the industry level, it enables the exclusion of natural resource–seeking FDI.

It is more difficult to distinguish between efficiency-seeking FDI and market-seeking FDI in the data, although differences across manufacturing industries can provide some indications. Take, for instance the classic GVC-intensive sectors that are characterized by a lead-firm network structure, and have been much studied – apparel, footwear and leather products, transportation equipment, and electronics (Sturgeon and Memedovic 2011). For apparel and leather products, China and Eastern European countries such as Bulgaria, Hungary, and Romania experienced a decline in the number of greenfield FDI projects in 2011–15 compared with 2003–07, while Ethiopia, Indonesia, Serbia, Myanmar and Vietnam experienced an increase (Hallward-Driemeier and Nayyar 2017). This suggests that FDI may have migrated from China to LMICs in Asia and Africa and from higher- to lower-wage locations in the Europe and Central Asia region. In the transportation equipment subsector, China, and countries in Europe and Central Asia experienced a decline in the number of greenfield FDI projects during 2011–15 relative to 2003–07, but certain large emerging economies such as Brazil, India, Mexico, and Thailand experienced an increase over the same period (map 2). This difference may reflect a predominance of efficiency-seeking FDI, whereby these countries provide the right combination of costs and capabilities, but it may also be linked to demand considerations, whereby countries with large domestic markets are attractive for FDI.

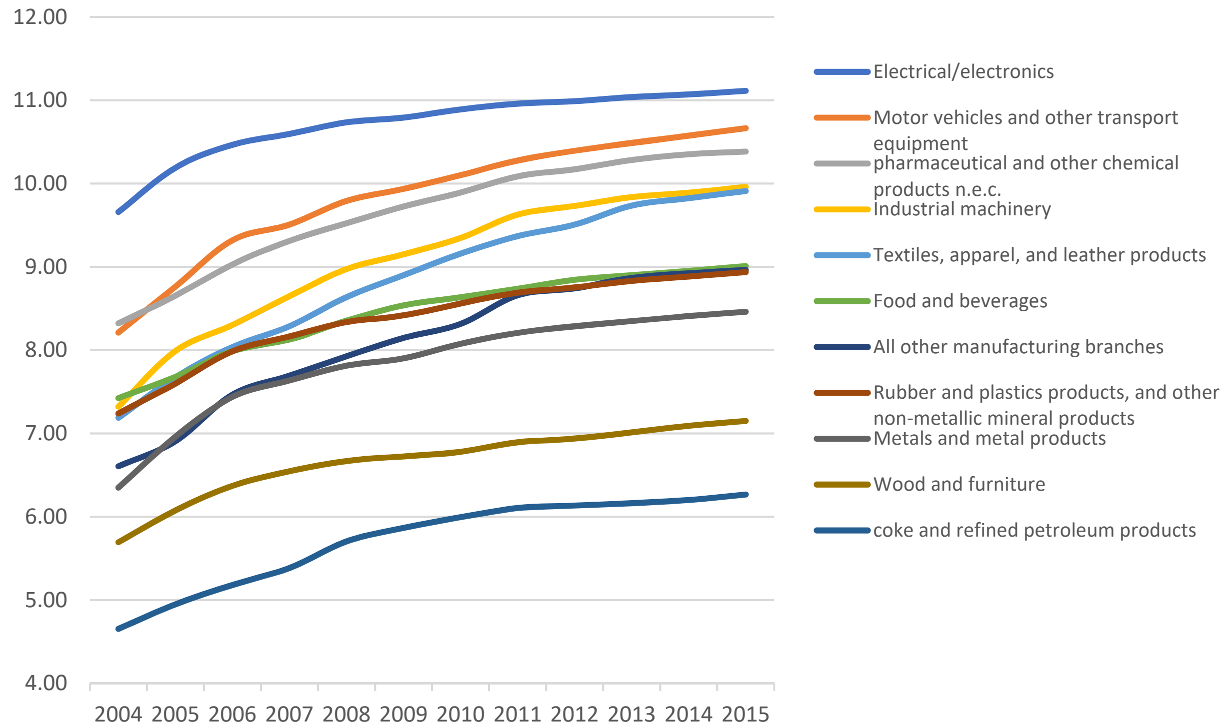
The cumulative flow of the number of FDI projects from high-income countries (HICs), as defined by the level of per capita GDP in 2003 (the first year in the data set) to low- and middle-income countries (LMICs), varies across both sectors and source countries. Figure 1 plots the evolution of greenfield FDI to LMICs by a given HIC between 2003 and 2015. It shows that while the cumulative flow of FDI projects to LMICs from all source HICs increased over this period, countries with the highest number of FDI outflows in 2003 remained so in 2015. This included the United States, Germany, France, and Italy. Portugal, Norway, Australia, and Singapore were among the HICs with the lowest number of (cumulative) FDI outflows both in 2003 and 2015. Spain experienced a discernible increase in its (cumulative) outflows to LMICs between 2003 and 2015. Figure 2 plots the evolution of greenfield FDI from HICs to LMICs across different manufacturing industries between 2003 and 2015. It shows that while the cumulative flow of FDI projects from HICs to LMICs increased across all industries over this period, sectors with the highest number of FDI outflows in 2003 remained so in 2015. This included GVC-intensive sectors such as electronics, transportation equipment, and apparel as well as pharmaceuticals. Commodity-based manufactures, including metal products, wood products, and coke and refined petroleum products recorded the lowest number of (cumulative) FDI outflows both in 2003 and 2015.

Figure 1: Cumulative Number of FDI projects from HICs to LMICs, by source country, 2004-2015 (natural logarithm scale)



Source: Calculations based on fDi Markets Database

Figure 2: Cumulative Number of FDI projects from HICs to LMICs, by sector, 2004-2015 (natural logarithm scale)



Source: Calculations based on fDi Markets Database

b) <u>Use of robots</u>

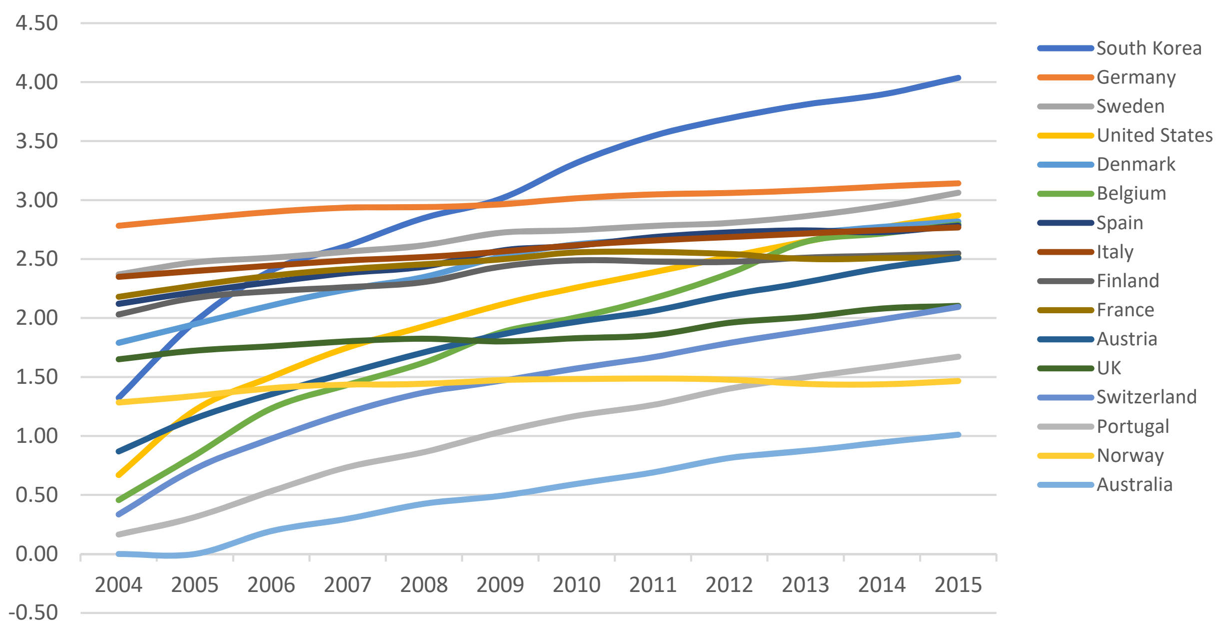
The data on industrial robots are taken from the International Federation of Robotics (IFR) database. It is the single source of data on the use of robots, which is comparable across countries and industries, and has been used by several studies in the literature that estimates the effect of automation on labor markets and other economic outcomes. High-income countries were the largest users of industrial robots in the manufacturing sector between 1995 and 2015. However, China is projected to have more than 400,000 industrial robots in operational stock in the manufacturing sector by 2018, more than doubling the number in 2015 (Hallward-Driemeier and Nayyar 2017). This would give China the distinction of having the highest number of installed industrial robots in the world, accounting for about one-fourth of total industrial robots projected to be installed globally. While other large emerging markets (including Brazil, India, Indonesia, Malaysia, Mexico, Thailand, and Turkey) also had nontrivial stocks of industrial robots in 2015 (appendix figure 2), Thailand leading the pack at approximately 14,000 robots was a fraction of China's at more than 200,000.

What matters more than the absolute stock of industrial robots is how the stock has changed, relative to labor input. These data on robots are combined with data on labor input taken from the World Input-Output Database Socio-Economic Accounts to compute the intensity of robot use, as measured by the stock of industrial robots per 1,000 employees. The intensity of robot use varies widely not only across sectors, but also across countries. Figure 3 plots the evolution of robot per

1,000 employees by country and shows that robot intensity in the manufacturing sector in 2015 was most advanced in the Republic of Korea, Germany, Sweden, the United States, Denmark and Belgium. Among these, the intensity of robot use increased discernibly between 2003 and 2015 in Korea, the United States, and Belgium, but remained largely unchanged in Germany and Sweden. Robotization remains more limited in Australia, Canada, and Portugal, though these countries are also increasing progressively the intensity of robot use in the manufacturing sector. Figure 4 plots the evolution of robots per 1,000 employees by sector. Electronics, automotive products, rubber and plastics, and metal products are the manufacturing industries in which robotization is most pronounced and has advanced most rapidly between 2003 and 2015. In contrast, the intensity of robot use in textiles, apparel, and leather products remains the most limited. These differences in the extent of robotization across industries reflect both the technological feasibility and commercial viability of adoption.

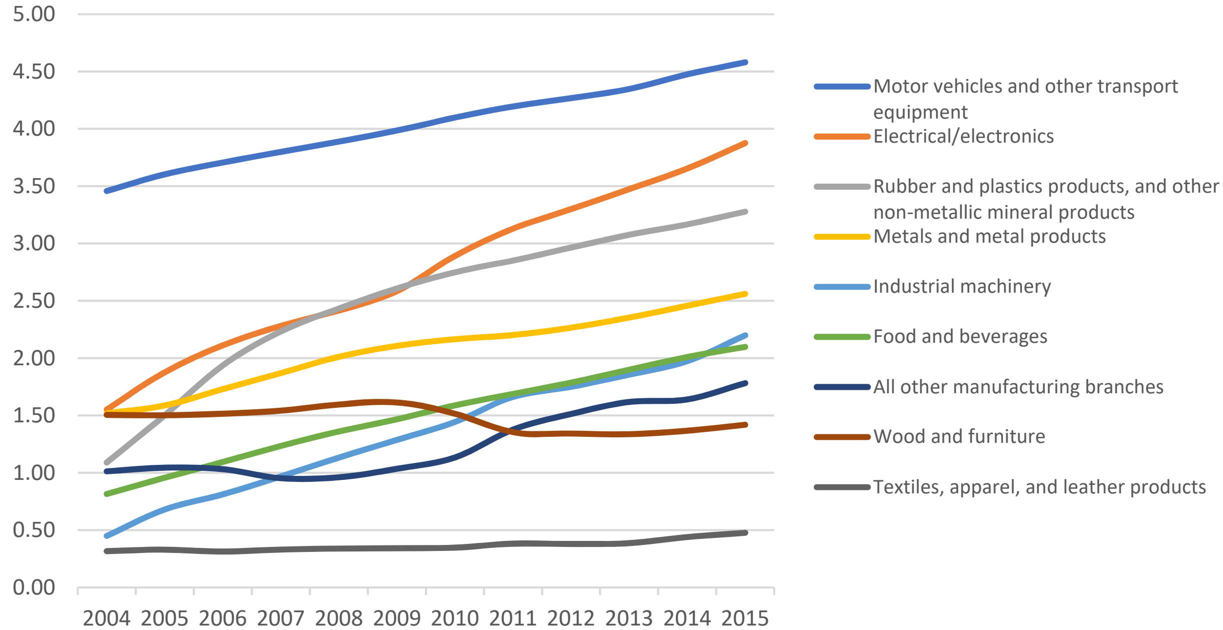
In sum, robot adoption has increased significantly over time, although at different speeds in different countries and sectors, which is convenient for identification. Appendix figures 3 and 4 display clearly the extent of variation in robot adoption across sectors, countries and time. It is particularly useful to compare electronics and textiles, apparel, and footwear – both GVC-intensive – which stand out as manufacturing industries where robotization in high-income countries advanced the most and least between 2003 and 2015. Figure 5 shows that robots per 1,000 employees in the electronics sector relative to apparel among HICs is negatively correlated with the flow of FDI from HICs to LMICs in the electronics sector relative to apparel between 2003 and 2015. This correlation naturally does not amount to causality but is indicative of a possible negative association between robotization in HICs and less offshoring to LMICs.

Figure 3: Operational Stock of Robots per 1000 Employees in HICs, by country, 2004-2015



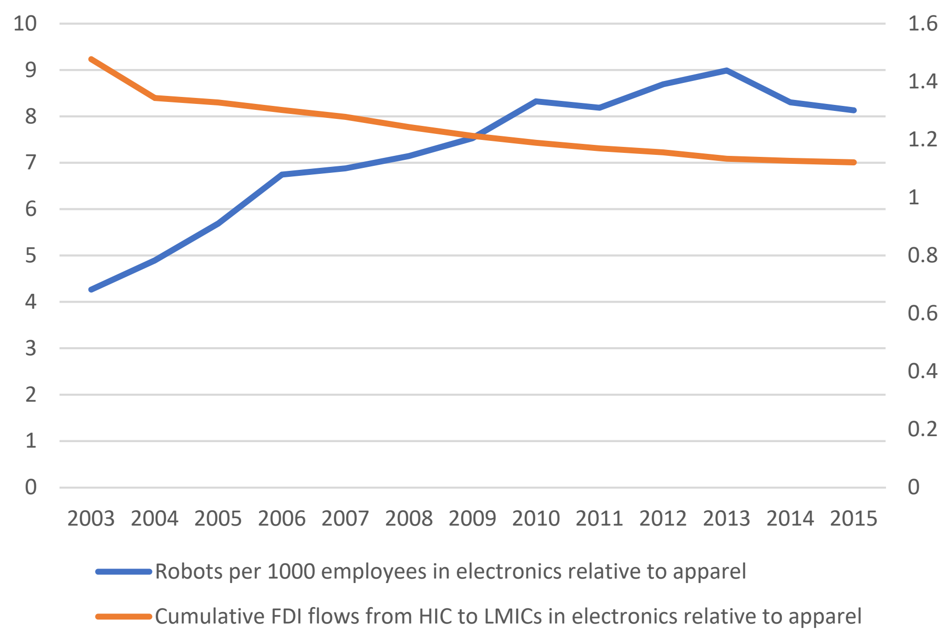
Note: Calculations based on International Federation of Robotics Database

Figure 4: Operational Stock of Robots per 1000 Employees in HICs, by sector, 2004-2015



Source: Calculations based on fDi Markets Database and International Federation of Robotics Database

Figure 5: Ratio of Robot Stock per 1000 Employees in Electronics to apparel in HICs and Ratio of Cumulative FDI Flows in Electronics to apparel from HICs to LMICs, 2003-2015



Source: Calculations based on fDi Markets Database and International Federation of Robotics Database

3. Empirical Strategy and Results

a) Specification and results

In order to analyze how the adoption of industrial robots in high-income countries may impact the flying geese paradigm, the empirical strategy examines the relationship between greenfield FDI from HICs to LMICs and the intensity of robot use in HICs. The number of greenfield FDI projects from high-income countries to low- and middle-income countries can be expressed as a function of the sector-specific intensity of robot use in source countries.[4] With the growth of robot use and differential use across sectors, we want to test for a non-linear relationship too. Formally, the following equation is estimated:

$$\ln(1 + FDI)_{ist} = \alpha + \beta_1 \ln(1 + Robots_{ist}) + \beta_2[\ln(1 + Robots_{ist})]^2 + \ln(1 + Exports_{ist}) + \gamma_{is} + \delta_{it} + \varepsilon_{ist} \tag{1}$$

FDI_{ijst} is the natural logarithm of the cumulative number of greenfield FDI projects from HIC country *'i'* to all low- and middle-income countries in sector *'s'* in year *'t'*. $Robots_{ist}$ is the intensity of robot use in HIC country *'i'* and $Robots_{ist}^2$ is the intensity of robot use in HIC country *'i'* squared. The intensity of robot use is calculated as the stock of robots per 1,000 employees and the squared term is included to test for a potential non-linear relationship between the intensity of robot use in HICs and FDI flows from HICs to non-HICs. $Exports_{ist}$ measures exports from HIC country *'i'* to all low- and middle-income countries in sector *'s'* in year *'t'* and is a proxy for the changing size of a sector over time across different HICs. Furthermore, the estimation equation includes country-sector and country-year fixed effects. Thus, the relationship being tested is how the growth in robot intensity in HICs is related to the growth in FDI stocks from HICs to LMICs.

The coefficient on the stock of industrial robots per 1,000 employees is positive and statistically significant and, taken on its own and ignoring the non-linear effect, shows that a 10 percent increase in the number of robots per 1,000 employees in HICs is associated with a 5.5 percent points increase in the growth rate of cumulative FDI flows from HICs to LMICs (table 2, column 1). At the same time, the coefficient on the stock of industrial robots per 1,000 employees-squared is negative and statistically significant (table 2, column 2). This suggests that, past a threshold, the continued robotization is associated with a statistically significant decline in the growth of FDI projects from HICs to LMICs. This negative non-linearity reverses, at least in part, the positive linear effect of robotization on FDI. At the mean level of robots per 1,000 employees (7.6), a 10 percent increase in the number of robots per 1,000 employees increases the growth rate of FDI by 1.8 percent (with the quadratic effecting offsetting about one-third of the positive linear effect). This non-linear relationship does not hold when the sample is restricted to FDI from HICs to low-income countries only. While the coefficient on the linear robot intensity term is positive and statistically significant at the 10 percent level, the coefficient on the quadratic robot intensity term is not statistically significant. What is also true is that the outflows of FDI to LICs are much lower; many HIC country-sector pairs have no outbound FDI to LICs and thus are perfectly identified by

[4] Japan is excluded from the analysis owing to non-comparable data series measuring the stock of industrial robots between 1993 and 2015.

the fixed effects and drop from the estimation. So, the news for LICs is that automation is associated with more FDI, but from a fairly limited base. The relationship between robotization and FDI flows from HICs to LMICs therefore largely derives from FDI going to middle-income countries (table 1, columns 3 and 4).

The maximum impact of automation on the growth in FDI is at just over 24 robots per 1,000 employees.[5] After that, continued robotization is associated with an increase in the growth of FDI but at a diminishing rate. However, less than 10 percent of the sample is above this threshold level of robots per 1,000 employees. The threshold level beyond which the growth in the intensity of robot use is associated with a decline in the growth of outbound FDI from HICs to LMICs is where the marginal impact of the quadratic term is greater than the linear term. At more than 500 robots per 1,000 employees,[6] this is not within the current range of data, as the maximum value for *ln (1+robots/1000 employees)* is 4.87 or 130 robots per 1,000 employees (table 1). Therefore, for approximately 90 percent of the sample, the increased intensity of robot use in HICs is associated with a rate of change in outbound FDI from HICs to LMICs which is increasing at an increasing rate.

The positive coefficient on the stock of industrial robots per 1,000 employees, which implies that the increasing intensity of robot use in HICs moved together with FDI from HICs to LMICs, is consistent with the literature which argues that many of the tasks that are suitable for automation are also suitable for offshoring (Autor, Dorn and Hanson 2015). For instance, routine tasks that follow explicit codifiable procedures are well suited to automation because they can be computerized, and well suited to offshoring because they can be performed at a distance without substantial loss of quality (Autor, Levy and Murnane, 2003). The result is also consistent with the "income" effect outweighing the "substitution" effect. On the one hand, robotization makes it economically profitable to re-shore some labor-intensive tasks to advanced economies. On the other hand, robotization leads to an expansion in the scale of production, which results in greater offshoring to low- and middle-income countries.

The non-linearity – whereby beyond a threshold level, the increasing intensity of robot use in HICs is associated with a deceleration in the rate of growth of FDI stock from HICs to LMICs – reflects the fact that the scale of use may be a significant factor in making robots economically attractive. Much like other physical capital, the cost associated with implementing a robot application in a particular industrial activity is largely fixed in nature and later installations of the same type can be made for a fraction of the initial cost. For instance, the initial planning, development, integration and installation for a robot workcell, on average, amounted to 40 percent of the robot system itself (Cyert and Mowery 1988). This is a source of significant economies of scale in robot use.

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[5] 3.18 in natural logarithm terms.
[6] 6.36 in natural logarithm terms.

b) Robustness checks

We now investigate the robustness of our baseline results to a range of different specifications and controls.

Given that the time period under consideration for our baseline estimation includes the financial crisis of 2008/2009, which originated in high-income countries, there is a possibility that the number of FDI projects from HICs to LMICs was influenced by associated cyclical variations. This is potentially of less concern here because the FDI variable in our estimating equation is expressed as a cumulative flow of FDI projects. Nevertheless, in order to account for a potentially confounding business cycle in identifying the impact of robot intensity in HICs on outbound FDI from HICs to LMICs, we divide our sample and re-estimate equation (1) for the pre-crisis (i.e. pre-2008) and post-crisis (i.e. post 2008) periods. The results suggest that the estimated impact of robot intensity in HICs on the rate of change of cumulative FDI flows from HICs to LMICs derives from the post-crisis period. The coefficients on robots per 1,000 employees and robots per 1,000 employees-squared are statistically insignificant in the pre-crisis period (table 3, columns 1 and 2).

Further, it may be argued that the results in the baseline estimation are being driven by the transportation equipment sector, which adopted considerably more robots per 1,000 employees than any other industry between 1993 and 2015. We therefore drop this sector from the estimation equation, leaving the robot intensity variable to capture variation across sectors other than transportation equipment. These estimates show that our results are not driven by the automobile industry alone, as the coefficients on the robots per 1,000 workers engaged and the robots per 1,000 workers engaged-squared terms remain, respectively, positive and negative, and statistically significant (table 3, column 2).

The role of China – which was excluded as a source country but included as a destination country in our estimation – also deserves closer attention. It may be argued that excluding China's outbound FDI, which has recently shifted from commodities to labor-intensive sectors in Africa and Asia for example, underestimates manufacturing FDI to lower-cost countries. It may also be argued that including China as a destination country can be driving the results. China was the major destination for FDI from high-income countries during the 1990s as production fragmented internationally into GVCs. However, the importance of parts and components imports in China's manufacturing exports – from the mid-1990s peak share of 34 percent to the current share of approximately 22 percent – has declined considerably in recent times (Constantinescu, Mattoo, and Ruta, forthcoming). This reflects the substitution of domestic for foreign inputs by Chinese firms (Kee and Tang 2015) and such value chain upgrading in China may have resulted in a trend decline in FDI. Yet, our results are robust to the inclusion of China as a source country and its exclusion as a destination country (table 3, column 4).

Sample selection notwithstanding, there is the additional concern that the association between the intensity of robot use in HICs and the number of FDI projects might reflect changes in the intensity of other forms of digital or data-enabled technologies. In order to asses this possibility, we control for the stock of ICT capital per 1,000 employees in our baseline specification. The coefficients on the robot intensity and robot intensity-squared terms remain, respectively, positive and negative and statistically significant (table 3, column 5).

c) Alternate (bilateral FDI) specification

We further analyze the robustness of our results by estimating equation (1) in the following specification which considers FDI from HICs to individual LMICs as destinations:

$$FDI_{ijst} = \alpha + \beta_1 Robots_{ist-1} + \beta_2 Robots_{ist-1}^2 + Exports_{ist} + ICT_{ist} + Imports_{ijst} + \gamma_{jst} + \mu_{ijt} + \varepsilon_{ist} \qquad (2)$$

FDI_{ijst} is the cumulative number of greenfield FDI projects from HIC country *'i'* to LMIC country *'j'* in sector *'s'* in year *'t'*. $Robots_{ist}$ is the intensity of robot use in HIC country *'i'* and $Robots_{ist}^2$ is the intensity of robot use in HIC country *'i'* squared; where the intensity of robot use is measured as robots per 1,000 employees. Following the baseline specification, $Exports_{ist}$ is a proxy for the changing size of a sector over time across different HICs and ICT_{ist} measures the changing intensity of ICT capital per 1,000 workers engaged.

Given that trade and FDI are two sides of the same coin in the organization of GVCs, offshoring is manifested either by MNCs setting up subsidiaries in lower-cost locations or by establishing arm's length contracts with firms there. The latter means that increased automation in HICs can affect exports from LMICs to HICs. And because FDI often facilitates the establishment of export platforms, the two are inextricably linked. Therefore, in order to control for this important source of endogeneity, equation (1) includes $ImExports_{ijst}$ – bilateral imports of HIC country *'i'* from LMIC country *'j'* in sector *'s'* at time *'t'* as an explanatory variable.

Furthermore, the estimation equation includes destination country-sector-year fixed effects as well as bilateral country pair-year and country pair-sector fixed effects. Destination country-sector-time fixed effects account for any time-varying FDI restrictions in a given sector in the destination country. They also reflect market-size effects that can help isolate efficiency-seeking FDI from market-seeking FDI. Country pair-year fixed effects allow for pair-specific shocks, such as exchange rate fluctuations, and absorb the role of variables routinely included in gravity models (e.g. output, distance etc.). They also control for any bilateral or multilateral trade and/or investment agreement as it varies over time.

The coefficient on the stock of robots per 1,000 employees remains positive and statistically significant, while the coefficient on robots per 1,000 workers engaged-squared remains negative and statistically significant (table 4). The magnitudes of these coefficients, however, are notably smaller which reflects the fact they measure the association between the intensity of robot use and bilateral FDI.

d) Instrumental variable estimation

Despite the robustness checks described above, the concern that use of robots is potentially endogenous remains. For example, it is feasible that the increased use of robots is a response to, rather than a cause of, changing FDI patterns; one may well imagine that increased globalization exerts a competitive pressure that incentivizes firms to innovate. There is also the possibility of omitted variable bias from source country-sector-time factors that affect both the use of robots and

flows of FDI. For example, the automobile industry in the United States may have adopted more robots over time, but it may also have experienced other shocks such as government bailouts.
To address this possibility of reverse causality, as well as biases caused by omitted variables or measurement error, we adopt an instrumental variables approach. In doing so, we follow Artuc, Bastos, and Rijkers (2019) in using industry-level trends in robot adoption in other countries with similar levels of income as instrument for a given country's robotization. Specifically, robot intensity is instrumented with robotization in the two most similar countries in terms of GDP per capita. This strategy follows closely that adopted by Acemoglu and Restrepo (2017) in their analysis of the local labor market impacts of robotization in the United States as well as subsequently by Artuc, Bastos and Rijkers (2019). Though not a panacea for all sources of omitted variable bias, this strategy allows us to focus on the variation that results solely from industries in which the intensity of robot use has been concurrent in the most similar economies. Further, we use the square of robot intensity in other countries with similar levels of income as an additional instrumental variable for the robots-squared term which is also potentially endogenous. We cannot formally test for the exogeneity of our instruments because the model is exactly identified. We can, however, test for instrument relevance through tests for under identification and weak identification. The instruments pass these tests in that they have explanatory power in predicting robotization.

Furthermore, both the positive linear and negative non-linear effects of robots per 1,000 workers engaged in HICs on FDI from HICs to LMICs remain intact (table 5). In fact, the quantitative impacts are somewhat larger. At the mean level of robots per 1,000 employees in the sample, the quadratic terms offsets about two-thirds of the linear effect whereby a 10 percent increase in the intensity of robot use increases the growth of FDI by 1.4 percent. While this could reflect possible measurement error, it is consistent with a large stock of FDI in a lower wage location providing a disincentive to automate at home. Now, the maximum impact of automation on the growth in FDI is at about 7.8 robots per 1,000 employees[7] and less than one-third of observations in the estimating sample are beyond this threshold. For much of the sample even here, therefore, further automation results in a diminishing rate of the growth of FDI, but not a decline. Beyond the threshold of 62 robots per 1,000 employees[8] is when the overall effect of additional automation results in a decline in FDI, but is met by less than 5 percent of the sample.[9]

The sign and statistical significance of the coefficients remains the same when the transportation equipment sector is dropped from the estimation as well as when China is included as a source country but excluded as a destination country. These results remain qualitatively similar when robot intensity is instrumented with robotization in the four most similar countries in terms of GDP per capita (table 6).

[7] 2.06 in natural logarithm terms.
[8] 4.12 in natural logarithm terms.
[9] These largely comprise the manufacture of transportation equipment in European countries such as Germany, France, Spain, Belgium, and Italy.

e) <u>Nearshoring</u>

There is also the question of whether the impact of increased robotization in high-income economies on FDI flows to low- and middle-income countries varies by the distance between the source and destination countries. Equation (1) is re-estimated to test this hypothesis, where the natural logarithm of the FDI stock is replaced by the share of FDI going to low- and middle-income countries in the same "region" (as defined by the World Bank country classification) as the dependent variable. The coefficients on the stock of robots per 1,000 employees and robots per 1,000 employees-squared terms are statistically insignificant (table 6, column 1). However, when the sample is restricted to countries in the Europe and Central Asia region, the coefficient on the stock of robots per 1,000 employees is negative and statistically significant (table 6, column 2). This suggests that robotization among Europe's high-income countries has been associated with the opposite of "nearshoring" and perhaps is indicative of the fact wages among LMICs in Europe were high relative to others. The non-linear relationship between the intensity of robot use and growth in the intra-region share of FDI remains statistically insignificant when the sample is restricted to Europe.

4. Conclusion

Anecdotes abound about how the use of labor-saving technologies associated with Industry 4.0 — such as robotics, the Internet of Things, and 3-D printing — might lead to the reshoring of production back to higher-wage locations. Even if high-income economies are not actively reshoring production, there are concerns that the use of industrial robots in established global centers of manufacturing may slow down opportunities for offshoring production to lower-cost locations. In going beyond anecdotes, we analyze the association between the intensity of robot use in high-income countries and greenfield FDI flows from high-income countries (HICs) to low- and middle-income countries (LMICs) to find that these fears are overblown.

Based on variation within country-sector pairs over time and between sectors for country-year pairs, we find a non-linear relationship – positive linear and negative quadratic – between the intensity of robot use in HICs and the growth of outbound FDI from HICs to LMICs between 2004 and 2015. This non-linear relationship, however, largely derives from FDI going to middle-income countries. For FDI to low-income countries, robotization in HICs has a weak positive impact; automation is associated with more FDI but the challenge is that the base of FDI in LICs is low. For some time, the stock of robots per 1,000 employees in HICs increased together with the growth in FDI from HICs to LMICs. But past a threshold, the continued robotization has a negative impact on the growth of FDI. In our preferred specification, more than two-thirds of the sample lies below this threshold level of robots per 1,000 employees, which suggests that the increased intensity of robot use resulted in the growth of FDI projects at an increasing rate for most country-sector pairs. For about 25 percent of the sample, the negative quadratic term indicates that the increased intensity of robot use in HICs has resulted in a deceleration of outbound FDI from HICs to LMICs. It is only 3 percent of the sample which exceeds the threshold level of robots per 1,000 employees beyond which the increased intensity of robot use leads to a decline in outbound FDI from HICs to LMICs.

Robots have therefore not grounded the flying geese, at least yet. At the same time, there are early warning signs as continued robotization beyond a threshold level has resulted in FDI growing more slowly than before. For the geese to fly unabated, lower-cost locations might need to walk the extra mile to remain attractive investment destinations. This means relying less on low wages only to be globally competitive but doing more to meet demanding ecosystem requirements in terms of infrastructure, logistics and other backbone services, regulatory requirements, trade restrictions, and so on. Automation has not yet changed the larger development agenda.

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Tables

Table 1: Summary Statistics, Country-Sector-Year Estimation Sample, 2003-2015

	Observations	Mean	Standard Deviation	Minimum	Maximum
ln (1+ FDI)	2,340	4.18185	1.909547	0	10.92664
ln (1+robots/1000 employees)	2,208	1.282001	1.204759	0	4.870358
ln (1+robots/1000 employees)^2	2,208	3.094315	4.481871	0	23.72038
ln (1+exports)	2,340	16.23891	1.500954	10.86253	19.63467
ln (1+ITstock/1000 employees)	1,275	0.944424	0.995507	0	4.960289

Table 2: OLS estimation

Dependent variable: Natural logarithm of (1 + stock of FDI projects)

	Full sample	Full sample	To low-income countries only	To middle-income countries only
	(1)	(2)	(3)	(4)
Ln (1 + Exports)	-0.0123	-0.0160	0.0525	0.0184
	(0.0415)	(0.0415)	(0.1026)	(0.0465)
Ln (1 + Robots per 1000 employees)	0.0551**	0.1329***	0.1624*	0.1722***
	(0.0224)	(0.0426)	(0.0985)	(0.0476)
Ln (1 + Robots per 1000 employees-squared)		-0.0209**	.0126673	-0.0187*
		(0.0098)	(.0235536)	(0.0109)
Country-sector fixed effect	Yes	Yes	Yes	Yes
Country-year fixed effect	Yes	Yes	Yes	Yes
R-squared	0.980	0.980	0.801	0.977
Observations	2,208	2,208	840	2,196

Table 3: Robustness checks

Dependent variable: Natural logarithm of (1 + stock of FDI projects)

	Pre-crisis period	Post-crisis period	Transport equipment sector excluded	China included as a source country, but excluded as a destination country	IT stock included as an explanatory variable
	(1)	(2)	(3)	(4)	(5)
Ln (1 + Exports)	-0.2291*	0.033	0.0139	.0281136	0.0079
	(0.1213)	(0.0359)	(0.0623)	(.0419495)	(0.0578)
Ln (1+ Robots per 1000 employees)	-0.1202	0.132***	0.3907***	0.1832***	0.2331***
	(0.1158)	(0.045)	(0.0845)	(0.0428)	(0.0688)
Ln (1 + Robots per 1000 employees-squared)	0.0553	-0.0179**	-0.1048***	-0.0293***	-0.0639***
	(0.0349)	(0.0103)	(0.0220)	(0.0101)	(0.0162)
Ln (1+ IT stock per 1000 employees)					-0.1086*
					(0.0588)
Country-sector fixed effect	Yes	Yes	Yes	Yes	Yes
Country-year fixed effect	Yes	Yes	Yes	Yes	Yes
R-squared	0.986	0.995	0.981	0.979	0.983
Observations	736	1,288	1,157	2,340	1,275

Table 4: Bilateral FDI

Dependent variable: Natural logarithm of (1 + stock of FDI projects)

	(1)	(2)
Total exports of source country	-0.0254	-0.0691***
	(0.0175)	(0.0248)
Exports from destination to source country	-0.0074***	-.0068683*
	(0.0028)	(.0036075)
Robots per 1000 employees	0.0724***	0.0649**
	(0.0181)	(0.0277)
Robots per 1000 employees-squared	-0.0107***	-0.0269***
	(0.0038)	(0.0061)
IT stock per 1000 employees		0.0044
		(0.0247)
Country pair year-fixed effect	Yes	Yes
Country pair sector-fixed effect	Yes	Yes
Destination country-sector-year fixed effect	Yes	Yes
R-squared	0.948	0.956
Observations	47,028	33,428

Table 5: Instrumental variable estimation

Dependent variable: Natural logarithm of (1 + stock of FDI projects)

	Full sample	Transportation equipment sector excluded	China included as a source country, but excluded as a destination country
	(1)	(2)	(3)
Exports	-0.0166	-0.0025	-0.0189
	(0.0604)	(0.0665)	(0.0605)
Robots per 1000 employees	0.4619***	1.0775***	0.4356***
	(0.1512)	(0.3595)	(0.1504)
Robots per 1000 employees-squared	-0.1118***	-0.3069***	-0.1093***
	(0.0369)	(0.1078)	(0.0367)
IT stock per 1000 employees	-0.1237*	-0.0672	-0.0032
	(0.0645)	(0.0832)	(0.0022)
Country-sector fixed effect	Yes	Yes	Yes
Country-year fixed effect	Yes	Yes	Yes
Observations	1263	1145	1263
(Centered) R-squared	0.982	0.979	0.982
Under identification test (Anderson canon. corr. LM statistic)	228.222	50.284	240.007
Weak identification test (Cragg-Donald Wald F statistic)	115.128	21.497	122.468
Instrumented	robots per 1000 employees, robots per 1000 employees-squared		
Instruments	robots per 1000 employees in the 2 most similar countries in terms of GDP per capita, robots per 1000 employees in the 2 most similar countries in terms of GDP per capita-squared		

Table 6: Instrumental variable estimation

Dependent variable: Natural logarithm of (1 + stock of FDI projects)

	Full sample	Transportation equipment sector excluded	China included as a source country, but excluded as a destination country
	(1)	(2)	(3)
Exports	-0.00367	0.0085	-0.0044
	(0.0586)	(0.0637)	(0.0586)
Robots per 1000 employees	0.2276**	0.6546***	0.2269*
	(0.1239)	(0.2284)	(0.1243)
Robots per 1000 employees-squared	-0.0793***	-0.2123***	-0.0778***
	(0.0286)	(0.0665)	(0.0286)
IT stock per 1000 employees	-0.0832	-0.0518	-0.0023
	(0.0613)	(0.0707)	(0.0021)
Country-sector fixed effect	Yes	Yes	Yes
Country-year fixed effect	Yes	Yes	Yes
Observations	1275	1157	1275
(Centered) R-squared	0.983	0.981	0.983
Under identification test (Anderson canon. corr. LM statistic)	366.909	127.493	366.162
Weak identification test (Cragg-Donald Wald F statistic)	213.133	58.638	212.525
Instrumented	robots per 1000 employees, robots per 1000 employees-squared;		
Instruments	robots per 1000 employees in the 4 most similar countries in terms of GDP per capita, robots per 1000 employees in the 4 most similar countries in terms of GDP per capita-squared		

Table 7: Nearshoring

Dependent variable: Natural logarithm of share of FDI among a "region pair"

	Full sample	Europe and Central Asia only
	(1)	(2)
Ln (1 + Exports)	0.0082	0.0189
	(0.0119)	(0.0123)
Ln (1 + Robots per 1000 employees)	-0.0181	-0.0444***
	(0.0119)	(0.0139)
Ln (1 + Robots per 1000 employees-squared)	-0.0042	0.0005
	(0.0028)	(0.0033)
Country-sector fixed effect	Yes	Yes
Country-year fixed effect	Yes	Yes
R-squared	0.866	0.883
Observations	2,021	1,741