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Robots Worldwide: The Impact of Automation on Employment and Trade

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Abstract

The impact of robots on employment and trade is a highly discussed topic in the academic and public debates. Particularly, there are concerns that automation may threat jobs in emerging countries given the erosion of the labour cost advantage. We provide evidence on the effects of robots on worldwide employment, including emerging economies. To instrument the use of robots, we introduce an index of technical progress, defined as the ability of robots to carry out different tasks. Robots turn out to have a significantly negative impact on worldwide employment. While it is small in developed countries, for emerging economies it amounts to -11 per cent between 2005 and 2014. However, here, there appear positive spillovers especially from robotisation in manufacturing on employment outside manufacturing. Furthermore, we assess cross-country effects, finding that robots in developed countries decrease off-shoring just as employment in emerging economies.

Zusammenfassung

Die Auswirkungen von Robotern auf Beschäftigung und Handel sind in der akademischen und öffentlichen Debatte ein viel diskutiertes Thema. Insbesondere gibt es Bedenken, dass die Automatisierung Arbeitsplätze in Schwellenländern gefährden könnte, da der Arbeitskostenvorteil nachlässt. Wir liefern Belege für die Auswirkungen von Robotern auf die weltweite Beschäftigung, einschließlich der Schwellenländer. Um den Einsatz von Robotern zu instrumentieren, führen wir einen Index des technischen Fortschritts ein, definiert als die Fähigkeit von Robotern, verschiedene Aufgaben auszuführen. Roboter wirken sich signifikant negativ auf die weltweite Beschäftigung aus. Während der Effekt in Industrieländern klein ist, beträgt er in Schwellenländern zwischen 2005 und 2014 -11 Prozent. Hier zeigen sich jedoch positive Spillover-Effekte insbesondere durch die Robotisierung im Verarbeitenden Gewerbe auf die Beschäftigung außerhalb des Verarbeitenden Gewerbes. Darüber hinaus untersuchen wir länderübergreifenden Auswirkungen. Dabei stellen wir fest, dass Roboter in Industrieländern zu weniger Offshoring führen und sich so negativ auf die Beschäftigung in Schwellenländern auswirken.

JEL

J23, O33, F16

Keywords

robot, technology, employment, off-shoring, re-shoring

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1 Introduction

Since several years, technological change dominates the discussions on the future of global labour markets. Digitization and automation give reason to expect that there will be major upheavals. One important dimensions of this technological change is robotisation. While the process already lasts for several decades, it is an enormous broadening of the tasks robots are conducting that makes robotisation a topical key issue. It is exactly this broadening of tasks, for which we provide clear-cut evidence, that we exploit in the underlying study in order to estimate the impact of robotisation on employment and trade.

The debate on the diffusion of robots is flourishingand it has provided already a number of studies. Scholars addressed the impact of robots on employment and tackled it either with country-industry panel setting Graetz/Michaels (2018); De Backer et al. (2018) or with more microeconomic approach using local labour market variation (Acemoglu/Restrepo, 2017; Dauth et al., 2017; Chiacchio/Petropoulos/Pichler, 2018) or firm-level information (Koch/Manuylov/Smolka, 2019) . Despite the high diffusion of robots in developing countries, however, research has focused mainly on developed countries. With our paper we use a country-industry panel setting to shed light on the role of robots in emerging economies and to analyse the impact of automation on the global organisation of production.

The evidence of the impact of robots on employment is ambiguous. Graetz/Michaels (2018) find no link between robots and overall employment in developed countries, while De Backer et al. (2018) show a positive correlation between robot investment and employment within MNEs in developed countries. Acemoglu/Restrepo (2017) show that one more robot per thousand workers negatively affects the US employment-to-population ratio by 0.37 %, while Chiacchio/Petropoulos/Pichler (2018) find a size of 0.16-0.20 percentage points in the EU. With a similar exercise, Dauth et al. (2017) find no detrimental role of robots for overall employment, while they see a compositional effect, namely, jobs lost in manufacturing are offset by new jobs in the service sector. Using firm-level data, Koch/Manuylov/Smolka (2019) find a net job creation in firms adopting robots of 10 per cent.

The ambiguity is likely explained by the fact that robots, that are one component of the wider automation wave, can not be solely the threat of current employment or the source of new employment. Rather, there are several channels through which automation can influence the production process and that have consequences on the labour market. Specifically, Acemoglu/Restrepo (2019) illustrate four mechanisms that counterbalance the displacement effect of automation: a productivity effect, a capital accumulation effect, the deepening of automation (operating through an increase of productivity) and the creation of new tasks. Furthermore, the authors point to potential risks related to the phase of automation (excessive automation) and to the capability of the labour market to adapt to the new required skills.[1]

This paper contributes to the literature in two ways. First, we are the first to present evidence on the impact of robots on employment in emerging economies. Evidence is still scarce, yet the diffusion of automation in middle- and low-income countries has been as pronounced as in high-income countries. They key point is that emerging countries display several labour market weaknesses - such as limited labour market institutions, high informality, large share of employment in agriculture - that could be connected to larger adverse effects of robots on employment in these countries. Moreover, robots are mainly used in manufacturing, a sector that represents the primary source of paid employment in emerging countries. Therefore we may expect an impact not only on the stock of employment but also on the overall quality of jobs.

Besides the effect of robots on employment, in this paper we assess to what extent robots affect off-shoring in high-income countries and we are the first to measure whether this matters for employment in middle- and low-income countries. Attention has been increasing as regards the tendency of bringing production back home to advanced economies, also known as re-shoring. In a developing literature, parallel work to our study (Faber, 2018; Artuc/Christiaensen/Winkler, 2019) finds negative impacts of robot exposure for the specific case of Mexican employment and US imports from Mexico. Increasing labour cost and the need of a shorter and more agile supply chain are among the factors that reduce the advantage of off-shoring the production in developing countries. For instance, China and Mexico experienced a wage increase of 500 per cent and 67 per cent during the last decades (Sirkin/Zinser/Rose, 2014). More recently, the trade conflict between China and the US is one of the key source of uncertainty for the economic growth in Asia (ILO, 2016). In this regard, firms in developed countries may find it cheaper to automate certain processes instead of running the production abroad (see UNCTAD, 2016). However, off-, re-shoring and automation are part of a more general rethinking of business strategies that have become more complex and based on a wider set of variables than simple cost comparisons. We may even see shoring going in opposite direction. In the study of Cohen et al. (2016), for example, the recovery of North America manufacturing is thought to be not due to re-shoring of US companies, but to off-shoring of Asian and European firms. In this complex and changing scenario, our paper looks at the role of robots in developed countries for the trade dynamics and employment in emerging countries.

Second. We propose a new instrumental variable approach that exploits a key reason why robots became so popular in the production process. That is their increasing ability of performing diverse and complex applications. Complementing human decision makers and pos-

[1] As regards this last point, see Warning/Weber (2018) on the consequences of digitalization on the hiring process. The authors find no impact of company-internal digitization on hirings and separations, while vacancies and abandoned searches increase.

sibly overcoming perceived short-comings in their decision making process is probably the key feature of the current technological wave. In the latter, robots play an important role and, above all, we know what they actually do.

Graetz/Michaels (2018) exploited the applications of robots by comparing the description of occupations in 1980 with the description of robot applications and generate a replaceability score of the occupations to instrument the stock of robots. Given that there are not comparable occupational classifications for emerging countries, we propose a new strategy that overcomes the lack of microeconomic data. This consists in exploiting the variation in the diffusion of robots across application. Data from the International Federation of Robotics (IFR) reveal that, between 1993 and 2015, robot have strongly increased their range of application. We show, for instance, that the applications with the largest share of robots in 1993 (e.g., arc welding or assembling) have been caught up in 2015 by new, fast-growing type of tasks (e.g., dispensing and packaging). While at the firm level the spread of robots in specific tasks can be endogenous to the type of labour force, we argue that at the country level such evolution depicts rather the advancement of the technological frontier of robots.

We rationalize this evolution by arguing that robots, as well as any technological tool, can experience two types of technological advancement: one that improves the tasks currently done (advancement at the intensive margin) and one that makes other tasks available (advancement a the extensive margin).[2] We make use of a stochastic specification to describe the two types of advancement and produce an index of technological advancement at the extensive margin based on the diffusion of robots across tasks. We find that this index is strongly correlated with the stock of robots, signaling a stronger advancement at the extensive margin rather than at the intensive margin. At the same time we are aware that our approach grasps part of all sources of endogeneity. Therefore, as a plausibility check, we compare our index with two proxies for related technological improvement: the price index of Information Communication Techonologies and the number of patents in automation. Both measures reveal a good correlation with our index.

We find the following results. First, robots have a detrimental effect on employment growth at the global level, more than eleven times stronger in emerging economies than in developed economies. Second, the impact of robots on employment is not affected by the level of labour intensity in developed economies, while the evidence on such non-monotonic effects is mixed for emerging economies. We get these results using an OLS approach applied to the long-run trend of the variables as well as with an IV approach intended to capture the endogeneity between employment and robots. Overall, our estimates point to a long-run decline of employment in the relevant sectors of about 5 per cent due to an increase of the number of robots of 24 per cent between 2005 and 2014. In developed countries, this decline of

[2] Acemoglu/Restrepo (2019) are the first to propose this distinction and to clarify the different implications for labour demand.

employment amounts to 0.43 per cent, while in emerging economies it reaches almost 11 per cent. However, we find that robotisation especially in manufacturing has substantial positive spillover effects on employment outside the sector in emerging economies, unlike in developed countries. Third, robots in developed countries reduce off-shoring and have an impact on employment in emerging economies of -8 per cent over 2005-2014.

The paper is structured as follows. In section 2 we provide a description of the dataset and the graphical evidence of the use of robots across sectors and countries. In section 3 we illustrate the theoretical basis of our main regression and that of our instrument. We show the diffusion of robots across applications and link it to our technological index of automation at the extensive margin. Following this, in section 4 we present the results of the impact of robots on employment in developed and emerging countries and discuss potential spillover effects between manufacturing and non-manufacturing sectors. Finally, in section 5 we provide the results of the analysis regarding the impact of robots on re-shoring in developed countries and the relative effect on employment in emerging countries. Section 5 concludes.

Table 1: Descriptive statistics by country, overall sample, 2014.

Country	Robots	Employees ('000s)	Average △ ln(VA) 2014-2000	Country	Robots	Employees ('000s)	Average △ ln(VA) 2014-2000
Japan	295829	53310	0.00	Turkey	6286	20049	0.07
United States	219434	145951	0.04	Switzerland	5764	4161	0.07
China	189358	858367	0.15	Indonesia	5201	74641	0.11
Korea, Republic of	176833	17547	0.07	Denmark	5119	2575	0.05
Germany	175768	38307	0.05	Hungary	4302	3834	0.08
Italy	59823	18127	0.04	Finland	4178	2196	0.05
Taiwan	43484	8308	0.03	Slovakia	3891	1896	0.11
France	32233	24545	0.05	Portugal	2870	3794	0.05
Spain	27983	15495	0.06	Russian Federation	2694	60265	0.14
United Kingdom	16935	26412	0.05	Slovenia	1819	745	0.06
India	11760	314882	0.11	Romania	1361	6171	0.12
Sweden	10742	4518	0.06	Norway	1008	2588	0.08
Brazil	9557	93704	0.09	Ireland	667	1593	0.07
Czech Republic	9543	4326	0.09	Greece	392	2625	0.04
Mexico	9277	25686	0.05	Bulgaria	197	2685	0.10
Netherlands	8470	7228	0.05	Croatia	121	1304	0.07
Canada	8180	16794	0.06	Estonia	83	561	0.11
Belgium	7995	3795	0.06	Lithuania	57	1157	0.10
Australia	7927	10669	0.09	Latvia	19	791	0.10
Austria	7237	3697	0.06	Malta	12	172	0.07
Poland	6401	12311	0.08				

Source: IFR and SEA (WIOD)

2 Data and descriptives

We obtain data on robots from the International Federation of Robotics (IFR). They refer to machines that 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” (International Organisation for Standardization, ISO). Our data for robots is available for 43 countries in seven broad sectors and 13 sub-sectors within manufacturing. To get data on employment, value added and capital input, we merge it with industry-level information available from the Socio Economic Accounts (SEA) of the World Input-Output Database (WIOD) and use market exchange rates provided by WIOD to convert nominal values into US dollars. After the merge we remain with 41 countries and 15 sectors. The time dimension is reduced to the span 2014-2005 because of data availability. Data for Mexico and Canada are included in the North America class before 2011. Therefore we impute them using the yearly growth rate of robots in Canada and Mexico after 2010.

By looking at the stock, table 1 shows that in 2014 robots were primarily installed in Japan, in the US, in the largest economies of the EU, but also in some developing countries, such as China, India and Brazil. The last column reports the average growth of value added between 2000 and 2014, but the evidence is mixed: within each of the two country groups, robots were installed in fast- as in slow-growth countries.

Given that robots perform their tasks at constant quality and almost an unlimited number of times, industries characterized by a large share of workers that carry out repetitive tasks, may find it profitable to substitute workers for robots. For this reason, we look at the change of robots between 2014 and 2005 together with the labour intensity in 2005, at the industry level. Table 2 reveals that, at the global level, robots spread as much in labour-intensive sectors as in capital-intensive sectors. This is particularly visible in emerging countries where automotive is more capital intensive, while in developed economies robots increased mainly in sectors such as automotive, basic metals and electronics , with a more intense use of labour.

In figure 1 we plot the time series of the stock of robots across countries to give a flavour of the evolution over time in both groups. We plot Japan and China in a separate graph due to their extreme values within their groups. Among developed economies, after Japan, Korea (Republic) emerges as one of the first investors of robots alongside the United States and Germany, while Italy reveals a declining trend. As regards developing economies, India, Brazil and Mexico show the highest level of stock, followed by a mixture of Asian and European countries and Russia. China stands out as the country that has bought more robots than any other country in the world since 2013 and is expects to expand even more, given the planned target of 100,000 robots per year by 2030.

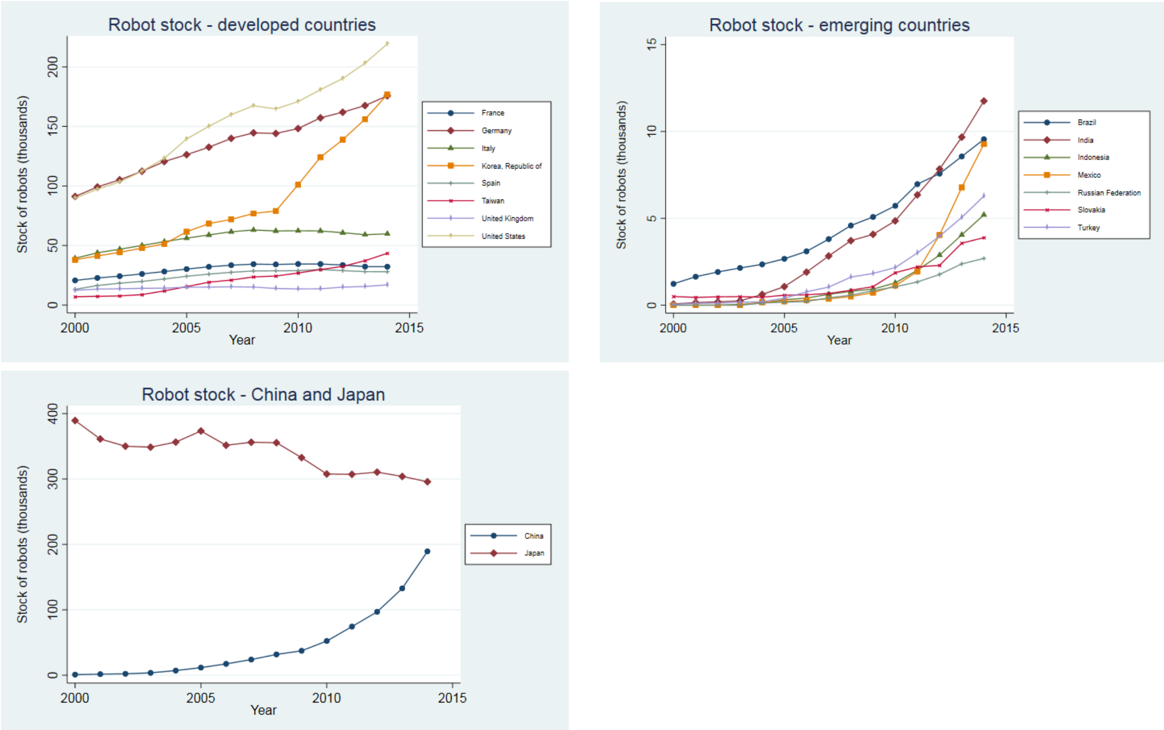
Table 2: Descriptive statistics by sector, overall sample.

Sector	World		Developed economies		Emerging economies	
	△ Robot stock 2014-2005	Labour intensity (2005)	△ Robot stock 2014-2005	Labour intensity (2005)	△ Robot stock 2014-2005	Labour intensity (2005)
Education/research & development	2	6.4	-21	6.5	64	6.2
Textiles	3	2.4	-2	2.4	17	2.3
Basic metals	1172	1.8	1257	2	940	1.2
Wood and Paper	-23	1.8	-39	2	22	0.9
Automotive	6019	1.6	5106	2.1	8509	0.1
Construction	28	1.6	29	1.8	25	0.9
Rubber, plastic and mineral products	733	1.4	201	1.6	2183	0.8
Industrial machinery	249	1.4	-64	1.2	1102	1.8
Electronics	3035	1.3	2995	1.4	3143	1.1
Food and beverages	749	1.1	878	1.3	397	0.6
Agriculture	13	0.9	14	0.6	9	1.6
Chimicals and fuel	306	0.8	383	0.8	96	0.8
Mining and quarrying	4	0.5	4	0.4	1	0.9
Utilities	1	0.4	-1	0.4	8	0.6

Source: IFR and SEA (WIOD)

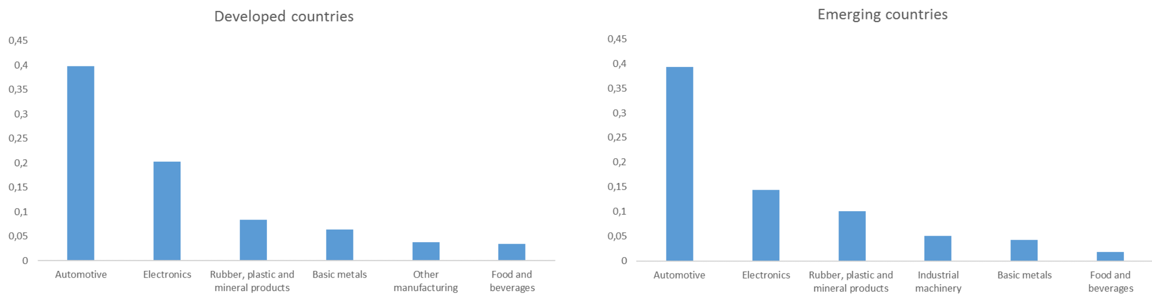
In addition, we present some descriptives at industry level. We follow the same classification as in Acemoglu and Restrepo (2017) and use those industries resulting from the merge with the SEA of WIOD. The striking fact of Figure 2 is that the distribution of robots across industries is almost identical in developed and emerging countries. In both sub-regions the installation of industrial robots regards essentially the manufacturing sector and is concentrated in the automotive industry.

Figure 1: Evolution of the stock of robots (in ’000s)



The figure shows time series of the robot stock in different countries. The three panels contain the data for the developed countries, the emerging countries and China and Japan. Source: IFR.

Figure 2: Share of robot by industry, developed and emerging countries (2014)



The figure shows how robots are distributed across industries. The shares are separately displayed for developed and emerging countries. Source: IFR.

3 Theoretical and empirical approach

3.1 Regression setting and econometric issues

We run our analysis assuming a standard Cobb-Douglas production function for output Y in sector i, country j and year t, $Y_{ijt} = L_{ijt}^{\alpha} K_{ijt}^{\beta}$. We log-linearize the production function and derive the labour demand as follows,

$$ln(L_{ijt}) = ln(\alpha) + ln(Y_{ijt}) - ln(W_{ijt}), \tag{3.1}$$

where W_{ijt} denotes the wage in sector i, country j, year t. We work with equation 3.1 and add as covariate the log of robot stock lnR_{ijt}. As we show in Section 2, robots increased more in labour-intensive sectors. Therefore we also include a dummy equal to one if the ratio employees/capital compensation in sector i, country j is larger than the country mean in year t, and zero otherwise. Following the approach of De Backer et al. (2018), we use this variable also in an interaction with robots. To avoid contemporaneous endogeneity, we measure the labour intensity at the beginning of the sample period, namely, 2005.

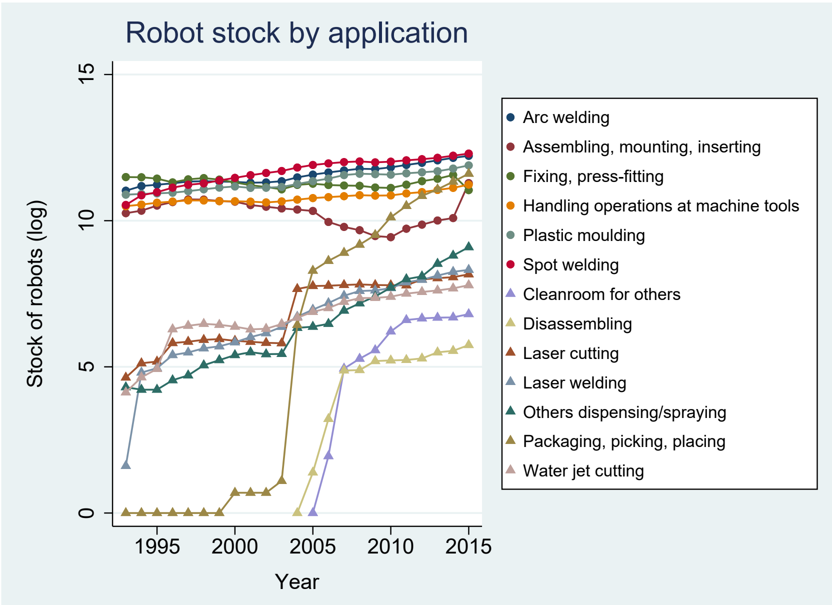
Moreover we have to deal with two other sources of potential endogeneity. First, in developed and emerging markets both employment and robot stock may be affected by transitory fluctuations of other factors connected to the stance of the business cycle, which would bias the estimated effect of robots upwards. To tackle this problem, we follow Karabarbounis/Neiman (2013) and use cross-country trends in the stock of employment and robots. This eliminates the influence of temporary contemporaneous shocks. Therefore, our estimation equation includes cross-sector trends of the variables in equation 3.1 and of the log of robots (that is why there will be no t subscript), the dummy for labour intensity in 2005, the interaction of robots with labour intensity, country and sector fixed effects:

$$L_{ij} = \gamma_0 + \gamma_1 Y_{ij} + \gamma_2 W_{ij} + \gamma_3 R_{ij} + \gamma_4 R_{ij} \times li_{05} + \gamma_5 li_{05} + X_i + Z_j + u_{ij}, \tag{3.2}$$

where X_i is the sector fixed effect, Z_j the country fixed effect and the other variables represent the linear trend in the log of the corresponding measure. While this estimates the employment effects within the sectors where robots are installed, we consider potential spillover effects between sectors below in section 4.2.

Second, reverse causality might be an issue. For instance, the abundance of workers may decrease the incentive to install robots. By the same token, financial frictions might limit both the usage of labour and robots alike, whereas foreign direct investments could alleviate such limitations. On the way to developing an instrumental variables approach, we start from the consideration that our estimation would be unbiased, if robot investments were exclusively the result of the intrinsic properties of this type of automation, such as its technological level and the tasks it can do. The IFR dataset provides the number of robots in each task (named ”application”) at country level. Robots are classified in 35 applications, clustered in 6 macro-classes: handling operations and machine tending, welding and soldering, dispensing, processing, assembling and disassembling, cleaning. A general trend that we detect from the data is that robot usage starts in few applications and over the years it spreads across all the other application. This reflects one facet of technological improvement of automation, namely, the practical ability of carrying out more and more tasks. It is also called ”automation at the extensive margin” (see Acemoglu/Restrepo, 2019) and it is key for displacement of workers. This is the opposite of advancements at the intensive margin, which takes place when a technological tool improves in the ability of doing what it currently does. Of course, the widening of robot usage across applications is not necessarily unbound from the structure of employment. For instance, the scarcity of cleaners and the abundance of assemblers could lead to more use of cleaning robots. However, this variation in robot usage would be exogenous to the aggregate level of employment.

Figure 3: Robot stock (log of) by application. In circle applications with top robot usage in 1993, in triangle application with top robot growth between 1993 and 2015.



The figure shows the (log of) robot stock between 1993 and 2015 for two sets of applications: those with highest robot usage in 1993 and those with the highest growth in robot usage between 1993 and 2015. Source: IFR.

Before presenting the analytical setting of our instrument, we provide a graphical evidence of advancement in automation at the extensive margin. In Figure 3 we compare the evolution of applications where robot usage is among the highest (top 25th percent) in 1993 with applications that experienced the largest (top 25th percent) increase of robots between the beginning of the series and 2015. No application is in both groups: this already indicates that the increase of the stock of robots goes hand-in-hand with a robotization across applications. The figure helps us visualize our reasoning about the instrument we are going to introduce, namely, if technological change makes automation spreading at the extensive margin, the increase of technical change correlates positively with a lower dispersion of robots across applications. Indeed the dispersion in 1993 for the selected application is much lower than in 2015, just as for all applications, which can however not be shown within one figure.

3.2 Instrumental variable

In order to motivate our instrument, we use a stylized analytical framework to explain the usage of robots depending on their technological frontier. To this purpose, we simplify the range of robots to type 1 and type 2, with each type corresponding to a certain task. In a stylized setting, the overall output of robots $Y_{R,t}$ shall be given by the CES production function

$$Y_{R,t} = \left[(\tau_{1,t}R_{1,t})^{\frac{\epsilon-1}{\epsilon}} + (\tau_{2,t}R_{2,t})^{\frac{\epsilon-1}{\epsilon}}\right]^{\frac{\epsilon}{\epsilon-1}} \tag{3.3}$$

where $R_{i,t}$ is the stock of robot i and $\tau_{i,t}$ its technological frontier in time t. The parameter ϵ describes the elasticity of substitution between the two types of robot, or tasks. We show later that our results do not depend on the degree of complementarity or substitutability of the tasks. We assume the product market of robots being competitive, therefore the price of robot P_i corresponds to its marginal product. Moreover, we are not interested in the absolute usage of robots, but rather in their relative demand (we provide the algebra in the Appendix), thus we write

$$\frac{R_{1,t}}{R_{2,t}} = \left(\frac{\tau_{1,t}}{\tau_{2,t}}\right)^{\epsilon-1} \left(\frac{P_{2,t}}{P_{1,t}}\right)^{\epsilon} \tag{3.4}$$

As usual, price shocks impact the usage of robots as predicted in a standard downward sloping demand curve. In particular, we use a stochastic specification of the technological frontier τ that allows us to generalize the advancement in technology in each type of robot. The laws of motion of technology are given by

$$\begin{aligned} \tau_{1,t} &= \tau_{1,t-1}(1+g_{1,t}) \\ \tau_{2,t} &= \tau_{2,t-1}(1+g_{2,t}) \end{aligned} \tag{3.5}$$

where $g_{i,t}$ is the technological shock of robot type i, with bivariate density function $(g_{1,t}, g_{2,t} \mid t-1) \sim F(\tau_{i,t-1}, \tau_{j,t-1})$. Here we distinguish between two technologies:

- one that advances with shocks to only one type of tasks in machines and generate automation at the intensive margin (*deepening of automation* in Acemoglu/Restrepo, 2019), with conditional expectation of $g_{1,t}/g_{2,t}$ given by the function

$$E(g_{1,t}/g_{2,t} \mid t-1) = f(\tau_{1,t-1}, \tau_{2,t-1}) \qquad \frac{df}{d\tau_{1,t-1}} > 0, \frac{df}{d\tau_{2,t-1}} > 0 \tag{3.6}$$

- another that proceeds by spreading and affecting more and more tasks (automation at the extensive margin), where the advancement in tasks i favors the advancement in task j. In this case, the conditional expectation of the relative shock are governed by

$$E(g_{1,t}/g_{2,t} \mid t-1) = f(\tau_{1,t-1}, \tau_{2,t-1}) \qquad \frac{df}{d\tau_{1,t-1}} < 0, \frac{df}{d\tau_{2,t-1}} > 0 \tag{3.7}$$

  Conversely to the first type of technological advancement, this last creates labour displacement.

In other words, in case of automation we condition the shock on technology i to the frontier of both technologies in time $t-1$, with the impact from an additional innovation to the frontier of i being smaller than the impact from an additional innovation to the frontier of j. This setting does not prevent infinite technological progress, but it foresees a challenge in improving further a technology relative to another one, when the first is leading in the technological frontier.

Now we explore which implications this model has on our demand for robots. With ϵ larger than one, i.e. robots being gross substitute, the relative demand of robots is described by equation (3.4). If $\tau_{1,t}$ is leading, i.e. it is the more advanced technology, then $R_{1,t} > R_{2,t}$ (up to price differences). For the property of the distribution function, τ_1 being the leader, τ_2 will tend to catch up. This will increase the demand for R_2 relative to R_1 and, by definition, reduce the dispersion of robots across the two classes. In case ϵ is smaller than one, namely, with robots being gross complement, if $\tau_{1,t}$ is leading, then $R_{1,t} < R_{2,t}$. For the same mechanism as above, further shocks to the technological frontier of the robots will make τ_2 catch up and R_1 increase, again with the result of reducing the dispersion.

Logically, this stylized approach suggests a negative correlation of technological change and robot dispersion, which we will exploit for instrumenting purposes. As a general multivariate measure for the dispersion we can use the standard deviation of the demand for robots. We present its derivation (algebra in the Appendix) in the case of ϵ larger than one and τ_1 leading,

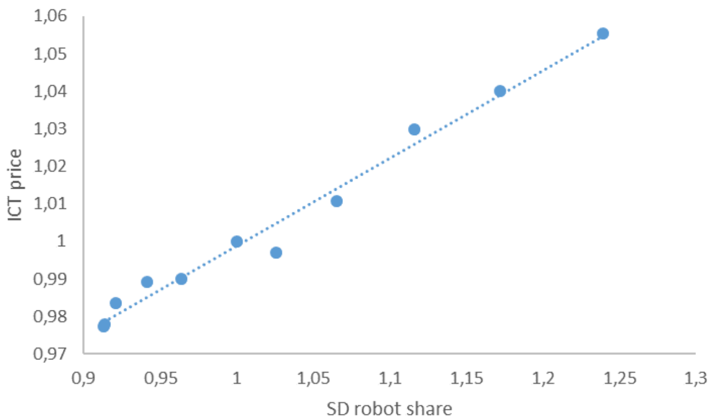
$$SD_{R,t} = Y_{R,t} \left(\frac{\tau_{1,t}^{\epsilon-1}}{P_{1,t}^{\epsilon}} - \frac{\tau_{2,t}^{\epsilon-1}}{P_{2,t}^{\epsilon}} \right) \frac{1}{2}. \tag{3.8}$$

Our data on applications are at country level. Therefore, for each country j we generate the share of robots in each application and we compute the index of technical progress TP_{jt} as the inverse of the standard deviation of the shares in year t. The logic behind is : the higher is the capability of robots of doing different tasks , the more even is their distribution among the applications, the lower will be the standard deviation, hence the higher will be the TP index.

3.3 Plausibility checks

In order to check the plausibility of this measure, we compare it with another technological input that has recently experienced a technological improvement, namely, Information Communication Technologies (ICTs)[1]. In particular we compare the average standard deviation of the robot shares with the average ICTs price index for a set of European countries and the US. The countries of the sample are Austria, Denmark, France, Germany, Italy, the Netherlands, Spain, United Kingdom, United States. The source of the ICT price index is EUKLEMS 2005-2015. Figure 4 shows the scatter plot of the two series. In order to avoid spurious correlation from both series trending downward, we compute the correlation of the residuals from regressing each variable on a constant and a linear trend. We get a value of 0.91.[2]

Figure 4: Standard deviation of robot share across applications versus ICT price index, 2005-2015 (2005=1).



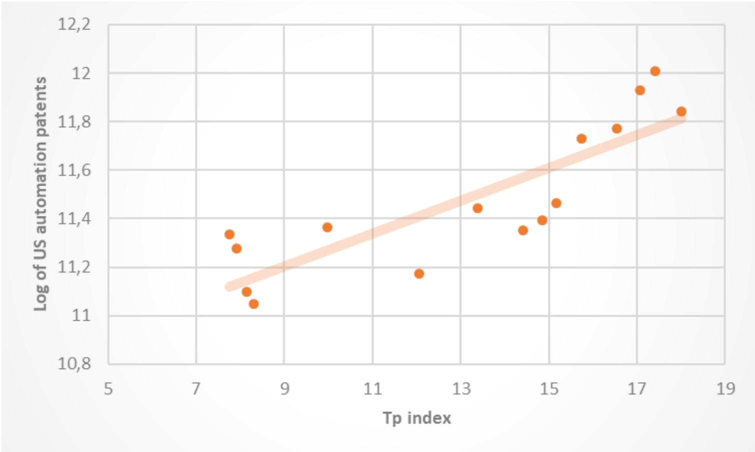
The figure shows scatter plot of the standard deviation of the robot share across applications versus the ICT price index. Source: IFR and EUKLEMS.

Lastly, given our assumption that robots are one example of a broader automation wave, we compare our TP measure with the number of automation patents, available for the US. Information on patents come from Google[3]. For the definition of *automation patent* we rely

[1] See Carbonero/Offermanns/Weber (2017) for the labour market implications of a declining ICT price.
[2] We have also computed the correlation on the first difference of each series: 0.74.
[3] http://www.google.com/googlebooks/uspto-patents.html

on Mann/Püttmann (2018): it represents a "device that carries out a process independently". According to the authors this definition embeds, among others, robots as well as self-driving vehicles. Figure 5 displays the two series normalized to 1 in year 2000. The evolution of both overlap significantly and the correlation is 0.83.

Figure 5: TP index versus automation patents, US 2000-2015 (2000=1).



The figure shows time series of the TP index and the automation patents in the US. Source: Mann/Püttmann (2018) and authors' calculations.

4 Results

4.1 Effects on employment

Table 3 displays the result for the OLS approach[1]. At a global level, robots has a coefficient of -0.034, statistically significant at one percent level. This means that an increase of ten per-cent in the stock of robots decreases employment in the relevant sectors by 0.34 per cent. To quantify the impact, the average increase of robots has been of more than 20 per cent, that implies a negative trend of employment of 0.7 per cent. The impact seems to be concentrated in labour-intensive sectors, for which the estimates point to a coefficient of -0.066. Moreover, the effect worldwide is most likely due to emerging countries, with a coefficient of -0.056. Here, given the change in robots between 2005 an 2014, we estimate a negative impact on employment of 2 per cent, mainly driven by labour-intensive sectors.

Table 3: Employment regressed on robot and labour intensity. OLS approach.

Dependent variable: employment	World		Developed countries		Emerging countries	
robot stock	-0.034^{***}	-0.004	-0.002	-0.001	-0.056^{**}	0.034
	(0.013)	(0.011)	(0.005)	(0.007)	(0.024)	(0.021)
robot stock × labour intensity		-0.066^{***}		-0.002		-0.145^{***}
		(0.014)		(0.008)		(0.018)
labour intensity	-0.005	0.017^{***}	0.003	0.003	0.004	0.045^{***}
	(0.004)	(0.006)	(0.002)	(0.003)	(0.006)	(0.007)
N	477	477	360	360	103	103
R^2	0.91	0.92	0.86	0.85	0.87	0.91

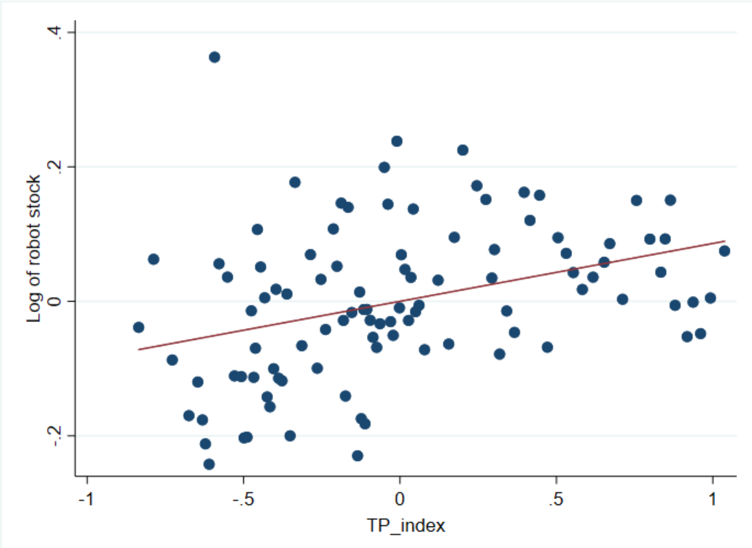
Regression using trend variables, that are the coefficients of regressions on a linear trend. Standard error clustered at sector-country level in parentheses. Significance levels: *, **, *** indicate significance at 0.10, 0.05 and 0.01. Controls: value added, wage, sector and country fixed effects. Estimates are weighted by sectoral employment in 2005. Source: IFR and WIOD.

Turning to the IV approach, we conducted a first-stage regression of the robot variable on our instrument and the other covariates from equation 3.2. Figure 6 is a binned scatterplot of the robots stock against our instrument TP index, once having residualized both for the control variables. Evidently, our instrument correlates positively with the robot stock. In a standard OLS regression, we get a positive coefficient of TP index of 0.14, significant at 1 per cent level. Moreover, TP index has a likelihood ratio test statistic of 39. Thus, we can build on a strong linkage between robots and the instrument.

In Table 4 we show the results of the IV approach. All the coefficients are larger (i.e. more

[1] In what follows, we exclude China. While the point estimates of the robot effects including China would be even larger, estimation uncertainty would be strongly inflated (results available upon request).

Figure 6: First stage regression of robot stock on TP index. Regression using trend variables between 2005 and 2015.



The figure shows the correlation between the trend in robot stock and the trend in TP index. Source: IFR.

negative) than those with OLS and, apart the one of the interaction, they turn out to be even more precise. The same difference appears in Graetz/Michaels (2018) using an alternative instrumenting strategy. Thus, there seems to be substantial upward bias in the OLS estimates due to reverse causality issues discussed in section 3. While we ague that our instrumented trend regression does a good job in accounting for the confounding factors, should there be any endogeneity left, the OLS-IV gap would even be underestimated.

Table 4: Employment regressed on robot and labour intensity. IV approach.

Dependent variable: employment	World		Developed countries		Emerging countries	
robot stock	-0.209^{***}	-0.247^{**}	-0.024^{**}	-0.051^{**}	-0.305^{***}	-0.054
	(0.056)	(0.125)	(0.009)	(0.021)	(0.048)	(0.456)
robot stock × labour intensity		0.046		0.038		-0.268
		(0.098)		(0.023)		(0.469)
labour intensity	-0.014^{***}	-0.029	0.003	-0.004	-0.038^{***}	0.050
	(0.005)	(0.033)	(0.003)	(0.006)	(0.010)	(0.159)
N	477	477	360	360	103	103
R^2	0.61	0.54	0.81	0.78	0.41	0.60

Regression using trend variables, that are the coefficients of regressions on a linear trend. Standard error clustered at sector-country level in parentheses. Significance levels: *, **, *** indicate significance at 0.10, 0.05 and 0.01. Controls: value added, wage, sector fixed effects. Estimates are weighted by sectoral employment in 2005. Source: IFR and WIOD.

The magnitude at a global level increases to -0.209 that implies a negative impact on overall employment in the relevant sectors over 2005-2014 of 5 per cent. For developed countries we get a negative effect on employment of 0.43 per cent, while for emerging economies our estimates point to a robots-driven reduction of employment of more than 11 per cent.

Assessing whether these impacts are comparable to those in the previous literature, we use the aggregate impact of robots on employment found by Acemoglu/Restrepo (2017), according to which one more robot reduces aggregate employment by 5.6 workers. We compute how many robots have been installed in the US between 2000 and 2014 and reduce employment by that amount multiplied by 5.6. We get a drop of employment of 0.52 per cent (or 0.57 per cent for all developed countries), very close to our baseline effect of 0.43 per cent.

4.2 Special effects within and outside manufacturing

Robots play a special role in manufacturing, but are also used in other sectors. This section takes a more detailed look at the employment effects of robotisation along the sectoral dimension. First, we seek to measure robots effects in manufacturing and the rest of the economy separately. Second, we will investigate spillover effects between the sectors.

According to our data, 85 percent of all robots are located in manufacturing. Besides manufacturing, our data show robot usage in utilities, construction, education and research, agriculture and mining.

For estimating separate effects in the two sectors, we interact the robots measure with an indicator dummy for employment observations stemming from manufacturing and from outside manufacturing. In particular, this allows for different coefficients in these two sectors. The results are shown in Table 5.[2]

The small negative employment effect in the developed countries that we determined above comes from job losses in manufacturing. Outside manufacturing, only a minor insignificant impact is estimated. In contrast, in the emerging countries, we find similar negative effects of robot usage both in and outside manufacturing. Furthermore, here, labour intensity plays an important role: The negative effects are of about three times the size in case of labour-intensive production (baseline effect plus interaction effect), and they are highly statistically significant.

Beyond sector-specific effects, potential spillovers between the sectors are of special interest. While job losses due to automation appear within the sectors where robots are used, effects across the sectors can mirror factors such as complementarities of robots and services or infrastructure, demand for capital goods or intersectoral labour supply shifts. For

[2] Here, China was included in order to increase the relatively limited number of observations at the sectoral level.

Table 5: **Robot stock within and outside manufacturing. IV approach.**

Dependent variable: employment	World		Developed countries		Emerging countries	
robot stock manufacturing	-0.142	-0.013	-0.033^{***}	-0.044^{**}	-0.297^{**}	-0.192
	(0.097)	(0.043)	(0.008)	(0.020)	(0.139)	(0.165)
robot stock non-manufacturing	-0.182^{*}	-0.006	-0.015^{*}	-0.035^{*}	-0.339^{**}	-0.180
	(0.111)	(0.050)	(0.009)	(0.20)	(0.141)	(0.191)
labour intensity	-0.003	0.069^{***}	0.002	-0.002	-0.002	0.127^{*}
	(0.009)	(0.014)	(0.001)	(0.004)	(0.012)	(0.066)
robot manufacturing $\times$ labour intensity		-0.201^{***}		0.012		-0.414^{*}
		(0.048)		(0.022)		(0.213)
robot non-manufacturing $\times$ labour intensity		-0.215^{***}		0.029		-0.334^{*}
		(0.040)		(0.022)		(0.171)
N	477	477	360	360	117	117
R^2	0.59	0.66	0.78	0.77	0.08	0.04

Regression using trend variables, that are the coefficients of regressions on a linear trend. Robust standard error in parentheses. Significance levels: *, **, *** indicate significance at 0.10, 0.05 and 0.01. Controls: value added, wage. Estimates are weighted by sectoral employment in 2005. Source: IFR and WIOD.

estimating the cross effects, we first calculate the average robot stock from manufacturing and non-manufacturing sectors, respectively. Then, we amend the baseline regression in Table 5 by manufacturing robots in the equations for non-manufacturing sectors and vice versa. This delivers the spillovers over and above the robot effects within sectors.

Table 6 contains the results. Formally, the variable *cross-sect robot stock* holds the cross effects in both directions, i.e. manufacturing robots in non-manufacturing equations and vice versa. In addition, *cross-sect robot stock manufacturing* stands for cross effects only from non-manufacturing robots on manufacturing employment.

In developed countries, we find no relevant interactions across sectors. This is in line with evidence from Acemoglu/Restrepo (2019) and Chiacchio/Petropoulos/Pichler (2018). A different result of positive spillover effects is found by Dauth et al. (2017) for Germany. However, our estimation outcome does not change when we exclude the US from the sample or consider only European developed countries. In contrast, in the emerging countries, robots in manufacturing have substantial positive spillovers on non-manufacturing employment. The reverse effects are also positive, but weaker. While our previous results have shown that robotisation strongly reduces employment in the emerging countries within the sectors of robot usage, the spillover results open up a certain perspective: importantly, robotisation in

Table 6: Spillover effect of robots across sectors. IV approach.

Dependent variable: employment	World	Developed countries	Emerging countries
cross-sect robot stock	0.186^{**}	-0.011	0.252^{***}
	(0.080)	(0.014)	(0.073)
cross-sect non-manufacturing robot stock	-0.090^{***}	0.002	-0.101^{**}
	(0.34)	(0.018)	(0.041)
labour intensity	-0.004	0.002	-0.006
	(0.003)	(0.002)	(0.007)
N	475	358	117
R^2	0.72	0.80	0.70

Regression using trend variables, that are the coefficients of regressions on a linear trend. Robust standard error in parentheses. Significance levels: *, **, *** indicate significance at 0.10, 0.05 and 0.01. Controls: robot stock in manufacturing, robot stock in non-manufacturing, value added, wage. Estimates are weighted by sectoral employment in 2005. Source: IFR and WIOD.

manufacturing is accompanied by the creation of non-manufacturing jobs. This is one crucial aspect when thinking about future paths of labour market development.

5 Further effects via off- and re-shoring

In this section we answer the following question: to what extent the internationalization of production has been influenced by the usage of robots? In particular, the significant difference in the impact of robots on employment growth between advanced and emerging countries begs the question whether the latter group suffers from automation because of their integration in global supply chains. The following analysis, therefore, aims at quantifying the effects of automation on employment conditioned on trade dynamics.

Indeed, there is a flourishing discussion dealing with potential shocks of off-shoring and reshoring on employment caused by the spread of automation both in developed and developing economies. UNCTAD (2016) argues that the historical labour cost advantage of low income countries might be eroded by robots if they become cheap and easily substitutable for labour. According to this scenario, the most affected industry should be manufacturing. This adverse effect might be strengthened by the growing labour quality in developing countries and the ensuing rise in labour costs. The Boston Consulting Group, for instance, reports that wages in China and Mexico increased by 500 per cent and 67 per cent between 2004 and 2014, respectively (Sirkin/Zinser/Rose, 2014). These and other issues might have pushed some companies, like General Electric and Plantronics, to shore the production back home (see, respectively, Crooks, 2012; Cattan/Martin, 2012).

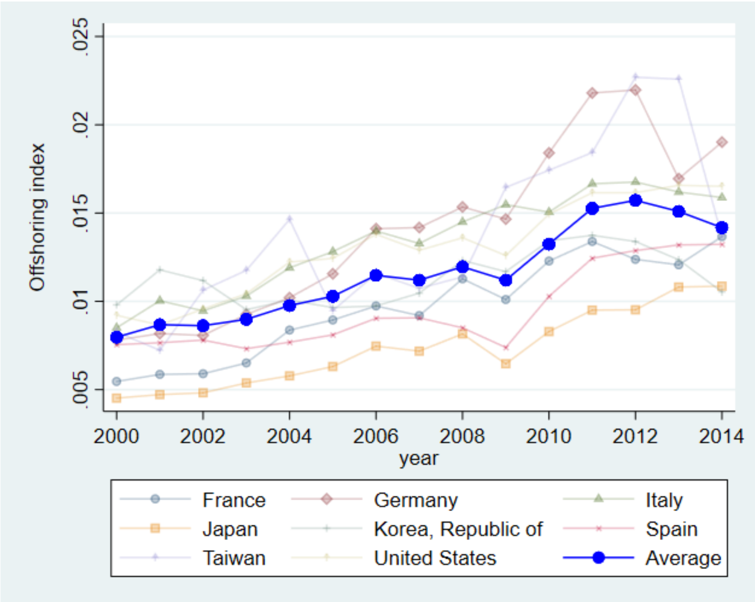
This convergence in cost competitiveness is likely to continue in the future, eroding the incentives for producers to move their activities from developed to developing countries. The results of a study of Gott/Sethi (2017) demonstrate that countries that have previously benefited from off-shoring will witness overall more job loss due to automation than onshore countries.

Nevertheless, it is claimed that off-shoring will keep on going at the same time. China remains the country receiving most of the investment flows. Even though labour cost has increased, indeed, developing countries experience also a rise of local markets with new needs and new demands. For instance, the Chinese middle class could potentially be bigger than the entire US population by 2020 (Atsmon/Magni, 2012).

In the empirical analysis we want to answer these questions: do robots reduce off-shoring in developed countries? If yes, does this harm employment in emerging countries? Regarding the first question, we compute the off-shoring index with respect to emerging countries as it is computed in the literature (e.g. De Backer et al., 2018), by using the share of imported non-energy inputs from emerging countries in total non-energy inputs. We conduct a similar analysis as for employment in subsection 4.1 except for the wage variable, for which we use a wage difference of developed country i with the wage of emerging countries weighted for the relative amount of imports with country i. Regarding the second question, for each sector of each emerging country we generate a variable that measures the stock of robots in the relative sector in developed countries, weighted by the flow of exports towards each sector in each developed country. This helps us assess the impact "abroad" of robots in developed countries taking into account the trade activity (in this way we control for those countries that installed many robots but have a low activity of import-export with emerging countries, and therefore are less pivotal for an employment effect there). We call this measure *trade-weighted robots* and we use it to explain employment in emerging countries (controlling for the domestic stock of robots). As for the first exercise, we use a wage difference of each emerging country with the set of developed countries, weighted by the trade activity.

Figure 7 displays the evolution of the off-shoring index for the countries with a number of robots in the top 25th percent in 2014. The amount of inputs imported from emerging countries passes from an average of 0.8 per cent to 1.4 per cent between 2000 and 2014. However, after years of persistent increase, since 2011 the trend falls back to a downward trajectory. As it visible from the graph, not all the countries experience this reversion alike. France, Spain and the US show rather a flattening of the off-shoring activity. However, except Japan, all countries in the sample witness a slowdown in the index. This reflects the phenomenon of re-shoring and is consistent with previous evidence in the literature (see for instance De Backer et al., 2016: for the media coverage of the re-shoring phenomenon).

Figure 7: Off-shoring index (relative to emerging countries) for countries with the highest share of robots in 2014.



The figure shows the degree of off-shoring for developed countries in the top 25th percentile of robot usage, between 2000 and 2014. Source: IFR and WIOD.

Table 7 display the results for the first analysis. The OLS approach delivers weakly significant positive results for the effect of robots on offshoring, while we don't get any further evidence from the interaction. As above, with the IV approach, we get more negative results. The impact is -0.073 significant at 5 per cent level. The coefficient is slightly larger than the one found by De Backer et al. (2018), the difference likely arises from the off-shoring index computed, in our paper, using only emerging countries [1]. As regards the interaction term, there seems to be no significant difference between labour- and capital-intensive sectors. Considering the increase of robots in developed countries between 2005 and 2014 leads to an impact on off-shoring of almost -1.3 per cent. Such a negative effect is in line with previous evidence and with the hypothesis that the use of robots may induce certain industries to reduce the amount of inputs produced abroad. The next step, then, is to check whether the lower share of imports caused by the spread of robots in developed countries has had any consequence on the level of employment in developing countries. For this, we use the trade-weighted robots measure.

Table 8 displays the results for the second analysis. The OLS estimation provides weak evidence of an effect of robots in developed countries on employment in emerging countries, with more insights from the interaction with labour intensity. Indeed, robots in developed countries seem to have a negative impact on employment in capital intensive sectors of emerging countries, while in labour intensive sectors the impact is slightly positive. Using an IV approach for tackling the problems of endogeneity, we get a larger negative effect. The coefficient for our trade-weighted robots is -0.459, significant at 1 per cent level. A change of trade-weighted robots in line with the change between 2005 and 2014, namely, 12 per cent is connected to a fall of employment of 5.5 per cent.

Table 7 and 8 established negative effects of robotization in developed countries on off-shoring in developed and on employment in emerging countries. We connect the two in a plausibility check, as re-shoring is likely to operate as a channel for the employment losses. We would expect that the drop in exports of the emerging countries resulting from Table 5 and the drop in the wage bill of the emerging countries resulting from Table 6 are of similar magnitude. The first effect may be a bit larger because, due to a labour share of about 50 per cent, part of the drop in exports would affect profits and not the wage bill. Since the off-shoring index is defined as the share of imported non-energy inputs in total non-energy inputs, we apply the IV effect of -0.073 percent from Table 5 to the value of non-energy inputs in developed countries imported from emerging countries, averaged over 2005-2014. This delivers 6.4 bn USD. Regarding the employment effect, we apply the IV estimate of -0.459 percent from Table 6 to the wage bill from the emerging economies averaged over 2005-2014. This delivers 4.8 bn USD. In view of the a-priori expectations explained above, we conclude that both estimates stand in a sensible relation.

[1] When we run the IV regression in Table 7 using off-shoring with imports from all the countries we get a coefficient of robots stock of -0.061, very close to their result.

Table 7: The impact of robots on off-shoring in developed countries.

Dependent variable: off-shoring in developed countries	OLS		IV	
robot stock	0.040^{**}	0.022	-0.073^{**}	-0.119^{*}
	(0.019)	(0.020)	(0.032)	(0.064)
robot stock × labour intensity		0.036		0.066
		(0.028)		(0.073)
labour intensity	-0.010	-0.017^{**}	-0.005	-0.017
	(0.007)	(0.008)	(0.007)	(0.012)
N	360	360	360	360
R^2	0.34	0.35	0.08	0.04

Regression using trend variables, that are the coefficients of regressions on a linear trend. Standard error clustered at sector-country level in parentheses. Significance levels: *, **, *** indicate significance at 0.10, 0.05 and 0.01. Controls: value added, wage difference. Estimates are weighted by sectoral employment in 2005. Source: IFR and WIOD.

Table 8: The impact of robots in developed countries on employment in emerging countries.

Dependent variable: employment in emerging countries	OLS		IV	
trade-weighted robot stock	-0.015	-0.125^{**}	-0.459^{***}	-0.319
	(0.045)	(0.060)	(0.155)	(0.235)
trade-weighted robot stock × labour intensity		0.132^{*}		-0.198
		(0.070)		(0.413)
labour intensity	-0.004	0.033^{***}	-0.004	0.014
	(0.004)	(0.008)	(0.009)	(0.040)
N	103	103	103	103
R^2	0.91	0.94	0.61	0.61

Regression using trend variables, that are the coefficients of regressions on a linear trend. Standard error clustered at sector-country level in parentheses. Significance levels: *, **, *** indicate significance at 0.10, 0.05 and 0.01. Controls: value added, wage difference, domestic robots, domestic robots interacted with labour intensity. Estimates are weighted by sectoral employment in 2005. Source: IFR and WIOD.

6 Conclusion

In this paper we present new evidence on the role of robots for employment and trade. In particular, we document that the use of robots is increasing rapidly in both developed and emerging countries. Given the globalisation of the supply chain, we also look at whether robots influence the trend in off-shoring in developed countries and, through that, employment in emerging countries. In other words, we explore whether the rise in robotization leads to re-shoring, i.e. the fact that firms in developed countries may find it more profitable to bring production back home after having it previously off-shored to low-cost, emerging economies.

We find that robots lead to a drop in global employment in the relevant sectors of 5 per cent between 2005 and 2014. The impact is rather low in developed countries, -0.43 per cent, but much more pronounced in emerging countries with about -11 per cent. However, we find that robotisation especially in manufacturing has substantial positive spillover effects on employment outside the sector in emerging economies, unlike in developed countries. These estimates come out using an instrumental variable approach where we use an index of technological progress of robots, defined as their ability to perform different tasks, to isolate the demand for automation. Indeed, this broadening of tasks arguably makes robotisation one of the key issues of recent technological change. We confirm the result of De Backer et al. (2018) with a more robust approach and show that robots reduce the trend in off-shoring. In this regard, we find that robotization in developed countries negatively affects employment in emerging countries, providing the first evidence of cross-country effects via robot-driven re-shoring. In sum, detrimental effect of robots on employment concentrate in developing countries, taking place both within-country and through the global supply chain.

All in all, it signals that if there are concerns about automation, and robots in particular, these should first and foremost address to low-income countries. This is in line with the alarms of the World Bank regarding the share of occupations subject to automation in middle- and low-income countries (see World Bank, 2016).

Evidently, this questions the conventional strategy of developing countries to grow by attracting low-pay manufacturing employment. Therefore, macroeconomic business models of emerging economies have to be rethought for the future. Exploiting positive spillover potential on jobs outside manufacturing depicts a promising path for labour market development.

Looking at robotization provides a good proxy regarding the impact of automation for mechanical tasks, which represents, however, only a subset of tasks currently carried out by human workers. Collection of data on artificial intelligence would allow to widen the analysis to a broader range of automation (see the discussion the impact of artificial intelligence on labour markets in Ernst/Merola/Samaan, 2018). This also concerns the impact of flexible and individualised production techniques on global value chains (compare Dachs/Kinkel/Jäger, 2019; De Backer/Flaig, 2017; Strange/Zucchella, 2017).

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Appendix

We provide the algebra for the derivation of the demand of robots. We assume the latter being exchanged in competitive markets, therefore we equate their marginal product to their price P_i. We start from equation 3.3

$$
\begin{aligned}
&Y_R = \left[(\tau_1 R_1)^{\frac{\epsilon-1}{\epsilon}} + (\tau_2 R_2)^{\frac{\epsilon-1}{\epsilon}}\right]^{\frac{\epsilon}{\epsilon-1}} \\
&\partial R_i : Y_R^{\frac{1}{\epsilon}} (\tau_i R_i)^{-\frac{1}{\epsilon}} \tau_i = P_i \\
&\qquad R_i^{\frac{1}{\epsilon}} = \frac{Y_R^{\frac{1}{\epsilon}}}{P_i} \tau_i^{\frac{\epsilon-1}{\epsilon}} \\
&\qquad R_i = \frac{Y_R}{P_i^{\epsilon}} \tau_i^{\epsilon-1}
\end{aligned}
$$

In order to illustrate our instrumenting variable, we compute the standard deviation of the demand for robot 1 and robot 2. Below we present the derivation of equation 3.8: we use the definition of the standard deviation and we plug in the demand for each type of robot

$$
\begin{aligned}
SD_R =& sqrt\left[\frac{\left(R_1 - \frac{R_1+R_2}{2}\right)^2 + \left(R_2 - \frac{R_1+R_2}{2}\right)^2}{2}\right] \\
=& sqrt\left[\frac{\left(\frac{R_1-R_2}{2}\right)^2 + \left(\frac{R_2-R_1}{2}\right)^2}{2}\right] \\
=& sqrt\left[\frac{(R_1 - R_2)^2}{4}\right] \\
=& \frac{R_1 - R_2}{2} = Y_R \left(\frac{\tau_1^{\epsilon-1}}{P_1^{\epsilon}} - \frac{\tau_2^{\epsilon-1}}{P_2^{\epsilon}}\right) \frac{1}{2}
\end{aligned}
$$

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