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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 statistically significant negative impact on worldwide employment. While it is small in developed countries, for emerging economies it amounts to -14% between 2005 and 2014. Furthermore, we assess cross-country effects, finding that robots in developed countries decrease off-shoring just as employment in emerging economies.

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

JEL classification: J23; O33; F16

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1 Introduction

The debate on the diffusion of robots is flourishing, with the number of studies rising constantly. Scholars particularly focused on the impact of robots on employment. We can summarize the approaches used to tackle this research question in two classes. Those using an industry-country panel setting (Graetz and Michaels, 2015; De Backer et al., 2018) and those looking at local labour markets (Acemoglu and Restrepo, 2017; Dauth et al., 2017; Chiacchio et al., 2018). Despite the high diffusion of robots in developing countries, however, research has focused mainly on developed countries. In the following paper we use the first approach 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, both within and between the two approaches. Graetz and Michaels (2015) 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 and Restrepo (2017) show that one more robot per thousand workers negatively affects the US employment-to-population ratio by 0.37 percentage points, while Chiacchio et al. (2018) find a size of 0.16-0.20 pp 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.

This paper contributes to the literature in two ways. We are the first to present evidence on the impact of robots on employment in emerging economies. While the diffusion of automation in middle- and low-income countries is similar to that in high-income countries, developing countries display several labour market weaknesses - such as limited labour market institutions, high informality, large share of employment in agriculture - that can be connected to larger adverse effect on employment in these countries. Moreover, attention has been increasing as regards the tendency of bringing production back home to advanced economies, also known as re-shoring. Indeed, 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. In this regard, firms in developed countries may find it cheaper to automate certain processes instead of running the production abroad (see UNCTAD (2016)). The implication would be a further detrimental effect on employment in middle- and low-income countries. In this paper we assess to what extent robots affect off-shoring in high-income countries and whether this matters for employment in middle- and low-income countries.

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. For that purpose, we propose a new instrument for the stock of robots that measures the degree of technological progress based on the capability of robots to carry out different tasks. Overall, our estimates point to a long-run decline of employment of about 1.3% due to an increase of the number of robots by 24% between 2005 and 2014. In developed countries, this decline of employment amounts to slightly over 0.5%, while in emerging economies it reaches almost 14%. Third, robots in developed countries reduce off-shoring, which has depressed employment in emerging economies by 5% between 2005 and 2014.

All in all, these results demonstrate that if there are concerns about automation, and robots in particular, these should first and foremost be addressed to emerging economies. This is in line with the warnings by the World Bank regarding the share of occupations subject to automation in middle- and low-income countries (see World Bank, 2016).

2 Background, data and descriptive statistics

There is no empirical consensus on the consequences of automation on employment. Mainly, this is related to the fact that there are several channels through which automation operates in the production process. Specifically, Acemoglu and Restrepo (2018) illustrate four mechanisms that might counterbalance the displacement effect of automation: a productivity effect, a capital accumulation effect, the deepening of automation (operating through an increase in productivity) and the creation of new tasks. Instead, the authors point to some risks related to the phase of automation (excessive automation) or to the capability of the labour market to adapt to the new required skills.[1]

The current literature has tackled the impact of robots on employment using two approaches. The first used a panel setting with data at the country-industry level and has found weak or no economic effects (see Graetz and Michaels, 2015; De Backer et al., 2018). The second looks at the role of robots for local labour markets and has found a detrimental effect in the US and the EU (see Acemoglu and Restrepo, 2017; Chiacchio et al., 2018).[2]

We use data on robots from the International Federation of Robotics (IFR) that refers 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 2005-2014 because of data availability. In the IFR database, information for Mexico and Canada is lumped together under "North America" before 2010. Therefore we impute them using the growth rate after 2010 applied to the share of robots at the sectoral level.

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 emerging economies, 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 both fast- and 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 robot density (robots per 10,000 workers) 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 mainly in high labour-intensive sectors. This is particularly visible in developed countries, while in emerging economies robots increased also in sectors

[1] As regards this last point, see Warning and Weber (2018) on the consequences of digitalization on the hiring process. The authors find that there is no impact on hirings and separations, while vacancies and abandoned searches increase.
[2] Except Dauth et al. (2017) who have found no effects for Germany.

such as working rubber, plastic and mineral products and industrial machinery that display a more intense use of capital.

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 emerging 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 installed more robots than any other country in the world since 2013 and is expected to expand even more, given the planned target of 100,000 robots per year by 2030.

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

Country	Robots	Employees ('000s)	Average Δ ln(VA) 2014-2005	Country	Robots	Employees ('000s)	Average Δ ln(VA) 2014-2005
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				

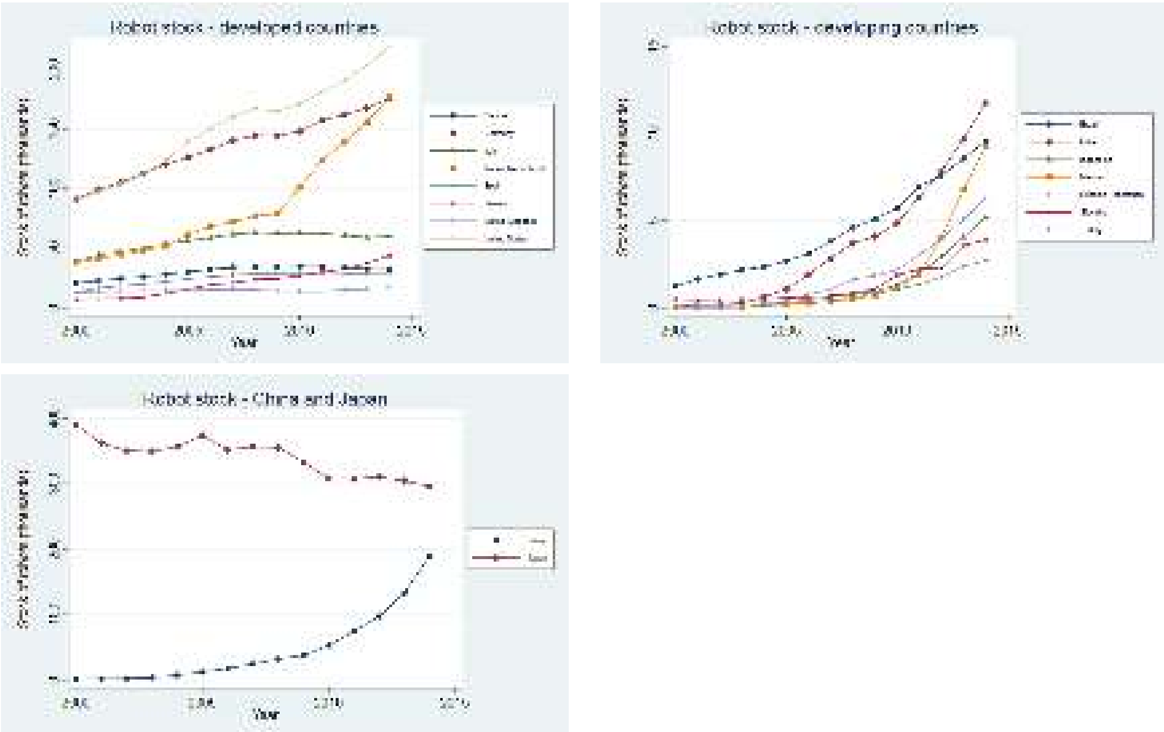
Source: IFR and SEA (WIOD)

Table 2: Descriptive statistics by sector, overall sample.

	World		Developed economies		Emerging economies	
Sector	Δ Robot density 2014-2005	Labour intensity (2005)	Δ Robot density 2014-2005	Labour intensity (2005)	Δ Robot density 2014-2005	Labour intensity (2005)
Agriculture	13	0.009	14	0.001	9	0.029
Electronics	3035	0.008	2995	0.003	3143	0.02
Wood and Paper	-23	0.007	-39	0.004	22	0.013
Automotive	6019	0.006	5106	0.003	8509	0.017
Construction	28	0.005	29	0.003	25	0.011
Textiles	3	0.004	-2	0.002	17	0.01
Rubber, plastic and mineral products	733	0.004	201	0.002	2183	0.008
Education/research/development	2	0.004	-21	0.002	64	0.008
Basic metals	1172	0.003	1257	0.003	940	0.005
Industrial machinery	249	0.003	-64	0.002	1102	0.007
Chemicals	306	0.002	383	0.001	96	0.004
Food and beverages	749	0.001	878	0.001	397	0.003
Utilities	1	0.001	-1	0	8	0.002
Mining and quarrying	4	0.001	4	0	1	0.001

Source: IFR and SEA (WIOD) .

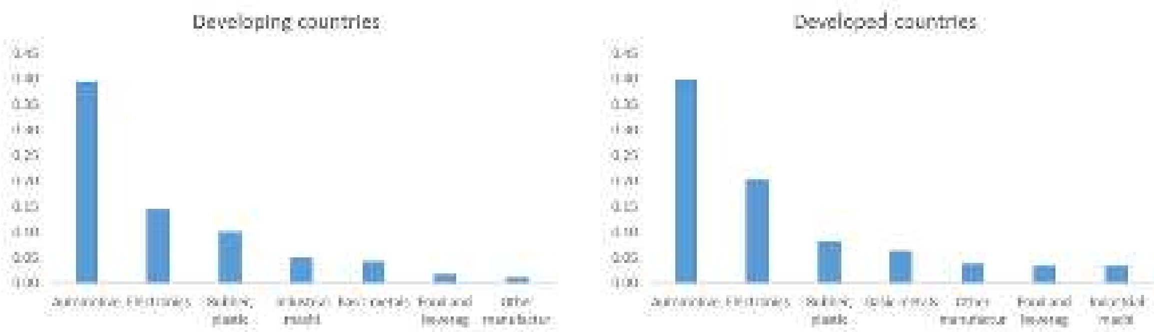
Figure 1: Evolution of the stock of robots (in ’000s)



Note: Selected countries.
Source: IFR.

In addition, we present some descriptive statistics at the industry level. We follow the same classification as in Acemoglu and Restrepo (2017) and use the industries that result 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 2: Share of robot by industry, developed and emerging countries (2014).



Source: IFR.

3 Methods and results

3.1 Employment

We run our analysis assuming that output Y in sector i, country j and year t is produced with a combination of only labour N and robots R, $Y_{i,j,t} = F(N_{i,j,t}, R_{i,j,t})$. Following standard derivations, denoting the wage in sector i, country j with W_{ij}, labour demand then results as:

$$N_{ijt} = F(Y_{ijt}, W_{ijt}, R_{ijt}), \tag{1}$$

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 stock 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 in an interaction with robots. To avoid contemporaneous endogeneity, we measure the labour intensity variable at the beginning of the sample period, namely, 2005.

We have to deal with two other sources of potential endogeneity. First, both employment and robot investment might be affected by transitory fluctuations over the course of the business cycle, which would bias the estimated effect of robots upwards. Second, reverse causality might be an issue. For instance, the abundance of workers may decrease the incentive to install robots. To tackle the first problem, we follow Karabarbounis and Neiman (2013) using the long-run trend of the log of each variable. This eliminates the influence of temporary contemporaneous shocks. Concerning the second source of endogeneity, 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. Accordingly, we instrument the stock of robots with an index of technological progress (TP) of robots at the country level. Concretely, we consider the capability of robots to carry out different tasks. This follows the idea that more and different tasks conducted by robots reflects relevant technological progress, whereas a concentration of more and more robots on the same task would rather correspond to capital deepening.[3] For this purpose, we make use of the data from IFR on the number of robots for each application, namely, their tasks. We compute the share of robots in each application and then compute the TP index as the inverse of the standard deviation of the shares in year t. The logic behind is that the higher is the capability of robots of doing different tasks and the more even is their distribution among the applications, the lower will be the standard deviation, hence the higher will be the TP index.

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).[4] In particular we compare the average standard deviation of the robot shares with the average ICT price index for a set of European countries and the US.[5] Figure A1 in the Appendix 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 obtain a value of 0.91.[6]

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[3] In a similar vein, Acemoglu and Restrepo (2018) distinguish the replacement of tasks from the enhancement of existing technology, defined as "deepening of automation". With the first, automation substitutes labour and harms labour demand, with the second it increases the productivity of tasks already automatized and may even increase labour demand.

[4] See Carbonero et al. (2017) for the labour market implications of a declining ICT price.

[5] 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.

[6] We have also computed the correlation on the first difference of each series: 0.74.

Finally, our estimation equation turns out to be the following:

$$N_{ij} = \beta_0 + \beta_1 robots_{ij} + \beta_2 robots_{ij} \times li_{2005} + \beta_3 li_{2005} + \beta_4 VA_{ij} + \beta_5 W_{ij} + u_{ij}. \quad (2)$$

We estimate equation 2 at the sectoral level using the merge of WIOD with IFR data between 2005 and 2014 with country and industry fixed effects.

Table 3 displays the result for the OLS approach. At the global level, the estimated effect of the stock of robots has a coefficient of -0.032, statistically significant at the 5% level. This means that a one percent increase in the stock of robots decreases employment by 0.054%. To quantify the impact, if the average number of robots increases by more than 20% as it has happened between 2005 and 2014, employment would fall by 0.8%. The impact is conditioned on labour intensity: labour-intensive industries reveal an impact that is more than one third larger than capital-intensive sectors. The effect is driven by emerging countries, with a coefficient of -0.031. Here, given the change in robots between 2005 and 2014, we estimate a negative impact on employment of 1.2%. In emerging countries, labour-intensive sectors are those mostly harmed by robots, with an estimated negative effect of 4.3%.

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

Dependent variable: employment	**World**		**Dev-ep countries**		**Dev-ing countries**	
robot stock	-0.032^{**}	-0.027^{**}	-0.000	-0.005	-0.031^{*}	-0.010
	(0.013)	(0.012)	(0.005)	(0.007)	(0.018)	(0.014)
robot stock × labour intensity		-0.037^{**}		0.012		-0.108^{***}
		(0.019)		(0.010)		(0.027)
labour intensity	-0.000	0.012	0.003	0.002	-0.010	0.055^{***}
	(0.005)	(0.008)	(0.004)	(0.004)	(0.008)	(0.013)
N	477	477	360	360	117	117
R^2	0.90	0.91	0.85	0.86	0.93	0.95

Regression using the trend variables, with country and industry fixed effects. Trends 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.

In Table 4 we show the results of the IV approach. All the coefficients are larger than those with OLS and they turn out to be even more precise. Thus, the negative employment effects of robots seem not to be driven by endogeneity issues. The magnitude at the global level increases to -0.055 that implies a negative impact on overall employment over 2005-2014 of 1.3%. For developed countries we get a negative effect on employment of 0.54%, while for emerging economies, our estimates point to a robots-driven reduction of employment of almost 14%.

Assessing whether these impacts are comparable to those in the previous literature, we use the aggregate impact of robots on employment found by Acemoglu and 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% (or 0.57% for all developed countries), very close to our baseline effect of 0.54%.

Given that we have data for industrial robots, we can also look whether the robots impact negatively manufacturing employment as a share of total employment. Table A1 in the appendix reveals a negative effect, stronger in emerging than in developed countries, but in both cases it is statistically weak.

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

Dependent variable: employment	World		Dev-ep countries		Dev-ing countries	
robot stock	−0.055**	−0.044**	−0.029***	−0.034***	−0.343***	−0.329
	(0.028)	(0.018)	(0.009)	(0.009)	(0.112)	(0.480)
robot stock × labour intensity		−0.023		0.012		−0.011
		(0.044)		(0.019)		(0.411)
labour intensity	0.007	0.015	0.002	0.001	−0.016	−0.010
	(0.008)	(0.015)	(0.005)	(0.005)	(0.021)	(0.217)
N	477	477	360	360	117	117
R^2	0.84	0.85	0.80	0.80	0.35	0.38

Regression using the trend variables, with country and industry fixed effects. Trends 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.

3.2 Off- and re-shoring

The second part of this paper seeks to answer the following question: to what extent has the internationalization of production influenced the role of robots in different countries? 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 re-shoring 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 et al., 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 and 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 A.T. Kearney demonstrate that countries that have previously benefited from off-shoring will witness overall more job loss due to automation than onshore countries (Gott and Sethi, 2017).

Nevertheless, off-shoring is likely to keep on going for some 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 and Magni, 2012).

In the econometric 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 similar to the literature 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 3.1 with an OLS and an IV approach. Regarding the second question, for each emerging country's sector, we construct a *trade-weighted robots* measure, i.e., we calculate a weighted stock of robots from the developed countries, where the weights are given by the share of exports to the specific country and sector. This measure is then used to explain employment in emerging countries (controlling for the domestic stock of robots).

Table 5 displays the results for the first analysis. Using the OLS approach delivers no significant effect of robots on off-shoring in developed countries. The interaction with labour intensity does not provide more precise estimates. However, the IV approach delivers a negative coefficient of -0.038 significant at the 5% level. As regards the interaction term, there seems to be no significant difference between labour- and capital-intensive sectors. According to these estimates, therefore, the increase of robots in developed countries between 2005 and 2014 leads to an impact on off-shoring of almost -0.7%.

Table 5: The impact of robots on off-shoring in developed countries.

Dependent variable: off-shoring in developed countries	**OLS**		**IV**	
robot stock	0.004	0.010	-0.038^{**}	-0.030^{**}
	(0.010)	(0.015)	(0.015)	(0.015)
robot stock × labour intensity		−0.013		−0.017
		(0.018)		(0.035)
labour intensity	−0.006	−0.004	−0.003	−0.001
	(0.004)	(0.005)	(0.005)	(0.007)
N	343	343	343	343
R^2	0.42	0.42	0.14	0.14

Regression using the trend variables, with country and industry fixed effects. Trends 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.

Such a negative effect is in line with previous evidence (see De Backer et al., 2018) 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 emerging economies. For this, we use the trade-weighted robots measure.

Table 6 displays the results for the second analysis. The OLS estimation provides scarce evidence and mimics the results of table 3 in the previous section. The IV estimation, instead, points to a coefficient for our trade-weighted robots of -0.431, significant at the 5% level. The change of that variable of 12% between 2005 and 2014 is connected to a fall of employment by 5%.

Table 6: The impact of robots in developed countries on employment in emerging countries.

Dependent variable: employment in emerging countries	**OLS**		**IV**	
trade-weighted robot stock	−0.014	−0.014	−0.431**	−0.341
	(0.063)	(0.052)	(0.173)	(0.809)
weighted robot stock × labour intensity		0.016		0.043
		(0.080)		(0.927)
labour intensity	0.008	0.058***	0.007	0.050
	(0.007)	(0.015)	(0.014)	(0.153)
N	113	113	113	113
R^2	0.94	0.79	0.96	0.86

Regression using the trend variables, with country and industry fixed effects. Trends 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, domestic robots, domestic robots interacted with labour intensity. Estimates are weighted by sectoral employment in 2005.

Tables 5 and 6 establish 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. Since the off-shoring index is defined as the share of imported non-energy inputs from emerging economies in total non-energy inputs, we apply the IV effect of -0.038 percent from table 5 to the value of total non-energy inputs in developed countries averaged over 2005-2014. This delivers 29 bn USD. Regarding the employment effect, we apply the IV estimate of -0.43 percent from table 6 to the wage bill from the emerging economies averaged over 2005-2014. This delivers 23.7 bn USD, quite close to the reduction of imports.

4 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, the trend in 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 have led to a drop in global employment of 1.3% between 2005 and 2014. The impact is rather small in developed countries, -0.54%, but much more pronounced in emerging countries with about 14%. These estimates are established 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 structural demand for automation from cyclical effects. 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, the detrimental effect of robots on employment is concentrated in emerging economies, taking place both within countries and through the global supply chain.

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 et al., 2018).

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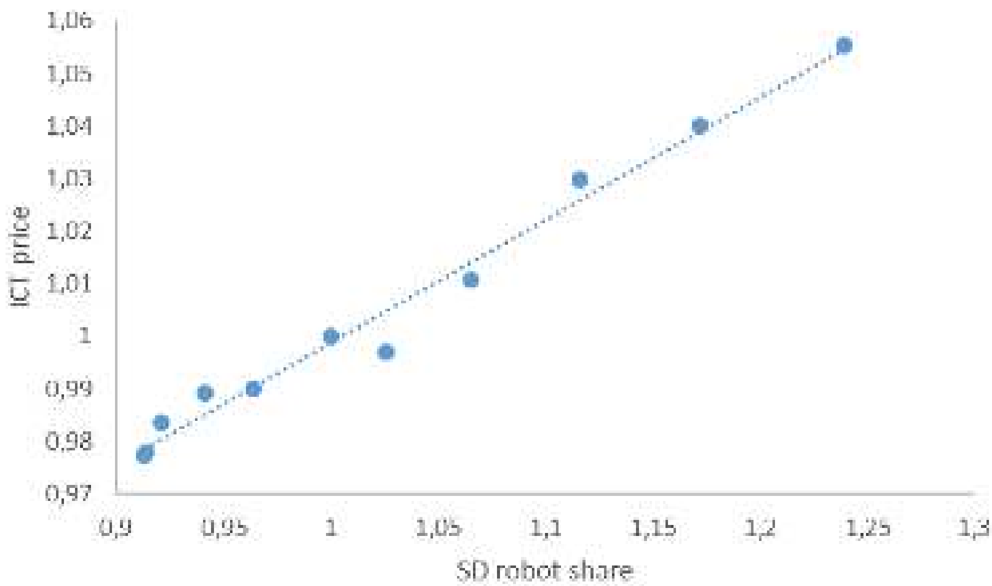
Appendix

Table A1: Impact of robots on manufacturing employment.

Dependent variable: Δ Manufacturing employment (in % of total employment)	OLS			IV		
	World	Dev' countries	Emerging	World	Dev' countries	Emerging
Δ Robot stock	−0.009	0.009	−0.030**	−0.046	−0.004	−0.072
	(0.10)	(0.006)	(0.011)	(0.030)	(0.009)	(0.054)

Standard error in parentheses. Significance levels: *, **, *** indicate significance at 0.10, 0.05 and 0.01. Controls: value added, wage, year fixed effects.

Figure A1: Standard deviation of robot share across applications versus ICT price index, (2005=1).



Source: IFR and EUKLEMS.