Is Automation Labor-Displacing in the Developing Countries, Too?: Robots, Polarization, and Jobs*

William F. Maloney† Carlos Molina‡

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Abstract: This paper uses global census data to examine whether the labor market polarization and labor-displacing automation documented in the advanced countries appears in the developing world. While confirming both effects for the former, it finds little evidence for either in developing countries. In particular, the critical category corresponding to manufacturing worker, operators and assemblers has increased in absolute terms and as a share of the labor force. The paper then uses data on robot usage to explore its impact on the relative employment evolution in each sample controlling for Chinese import penetration. Trade competition appears largely irrelevant in both cases. Robots, however, are displacing in the advanced countries, explaining 25-50 percent of the job loss in manufacturing. However, they likely crowd in operators and assemblers in developing countries. This is likely due to off-shoring that combines robots with new operators in FDI destination countries which may, for the present, offset any displacement effect. Some evidence is found, however, for incipient polarization in Mexico and Brazil.

Keywords: Labor Market Polarization, Robots, Automation, Trade Competition.
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†World Bank, Washington, DC 20433, United States. Corresponding author E-mail: wmaloney@worldbank.org
‡Department of Economics, M.I.T. E-mail: carlosmolinaguerra@gmail.com>
1 Introduction

Advanced country labor markets have sharply polarized over the last two decades. For the US, Katz et al. (2006); Autor (2010); Autor and Dorn (2013) document expanding job opportunities in both high-skill, high-wage occupations and low-skill, low-wage occupations, coupled with contracting opportunities in middle-wage, middle-skill white collar and blue-collar jobs. Of particular interest, job opportunities are declining in middle-skill, blue-collar production, craft and operative occupations. Goos et al. (2014) document that this phenomenon has appeared in each of 16 European countries from 1993 to 2006. Even growth optimists, such as Brynjolfsson and McAfee (2014) predict major shifts in the composition of labor and the need for compensatory social policies to offset the resulting inequality.

Leading explanations include the ongoing automation and off-shoring of middle-skilled “routine” tasks that were formerly performed by workers with moderate education. Routine tasks as described by Autor et al. (2003) are sufficiently defined that they can be carried out by a computer executing a program or alternatively, by a comparatively less-educated worker in a developing country who carries out the task with minimal discretion, such as repetitive assembly tasks. Generally, the literature has emphasized automation change over trade forces. Autor argues that the general wisdom by the end of the 1990s was that trade flows were simply too small to explain the vast changes in skill demands and wage structures and Acemoglu and Autor (2011) suggest this empirically as well. David et al. (2013) for instance, specifically measure the impact of the rise in China and find that, while not negligible, it accounts for only 25% of the fall in manufacturing employment in the US. Though, recent work (Acemoglu et al., 2016) suggests larger impacts than previously thought, a major focus remains on automation and, in particular, robots.

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1 The role of technology is central, but also may have different implications than traditionally thought. Acemoglu and Autor (2011) offer a model where technological progress does not necessarily raise earnings in all sectors as in the standard models, but where machines substitute for tasks previously performed by labor leading to polarization and real earnings falls.
The recent empirical literature from the US and Europe finds the increasing stock of robots indeed displaces manufacturing workers, although it may not adversely affect total employment. Acemoglu and Restrepo (2017, 2019) find that increased robot usage between 1990 and 2007 on US local labor markets led to large and robust negative effects on employment and wages. Dauth et al. (2017) find for Germany that robots account for almost 23 percent of the overall decline of manufacturing employment over the period 1994-2014, but this loss was fully offset by additional jobs in the service sector. Graetz and Michaels (2018) find that within the EU, industry level adoption of industrial robots had no measurable effect on overall labor hours and modestly shifted employment in favor of high-skill workers and away from lower skill workers. Gregory et al. (2016) looking at 238 European regions find that routine-replacing technological change (RRTC) does have a substitution effect for production workers that is more than offset by the services sector. Autor and Salomons (2018), drawing on 28 industries for 18 OECD countries since 1970, find that productivity instrumented by robots negatively impacted both hours worked and labor’s share of output.

The concerns for developing countries are potentially farther reaching. In China and Mexico, local installation of robots has had significant displacement effects (Giuntella and Wang, 2019), Cortes and Morris (2019) and Artuc et al. (2019). However, in addition, as...
automation eliminates routine manufacturing type jobs, or as it permits ‘reshoring’ tasks, we may see a short circuiting of the traditional forces generating the “flying geese” pattern where stages of the value chain are passed down from advancing to follower countries and it is unclear whether developing countries have the necessary complementary skills to attract the parts of the chain that still require workers. Though Hallward-Driemeir and Nayyar (2019) find that increased automation in advanced countries in general has not led to a declining growth rate in outward oriented FDI, there is some incipient evidence for this effect. For instance, Faber (2018) and Artuc et al. (2019) find Mexican exports to the US declining with increased US robot use and a concomitant fall in manufacturing employment most susceptible to automation, although the latter finds no overall decline in manufacturing employment.

The present paper uses global census data to explore whether patterns of polarization are visible in the developing world and the role of automation, proxied by robot adoption, in driving the patterns in both groups of countries. Section 2 discusses why we might find differing patterns between the advanced and developing countries and Section 3 discusses the data sources. Section 4, broadly following Autor (2010), tracks job categories across time for the advanced countries and 21 developing countries in Africa, Latin America and Asia and confirms the polarization patterns for the former, but not the latter. Previous work,

any other country by 2017. Part of this investment may reflect the dramatic fall in robot prices. The payback period for a welding robot in the Chinese automotive industry, for instance, dropped from 5.3 years to 1.7 years between 2010 and 2015, and by 2017 was forecast to shrink to just 1.3 years. However, in addition, both the Chinese and Korean governments now subsidize the introduction of robots. See http://www.bloombergview.com/articles/2015-04-09/robots-leave-behind-chinese-workers

While China has complemented this trend with investment in training for more complex jobs, recent college graduates report having problems finding employment and 43% consider themselves over-educated for their positions, much as Beaudry et al. (2013) suggest is happening in the US. “That might not be a problem if the Chinese economy were generating plenty of higher-skill jobs for more educated workers. The solution, then, would simply be to offer more training and education to displaced blue-collar workers. The reality, however, is that China has struggled to create enough white-collar jobs for its soaring population of college graduates. In mid-2013, the Chinese government revealed that only about half of the country’s current crop of college graduates had been able to find jobs, while more than 20 percent of the previous years graduates remained unemployed. According to one analysis, fully 43 percent of Chinese workers already consider themselves to be over educated for their current positions. As software automation and artificial intelligence increasingly affect knowledge-based occupations, especially at the entry level, it may well become even more difficult for the Chinese economy to absorb workers who seek to climb the skills ladder”. See http://www.nytimes.com/2015/06/11/opinion/chinas-troubling-robot-revolution.html
broadly following Goos et al. (2014), WorldBank (2016) and using ILO Kilm data finds evidence that middle skilled occupations intensive in routine cognitive and manual skills have also decreased across the developing world as a share of the workforce with the exception of China, Ethiopia, Argentina and Nicaragua. Our picture is more mixed, offering less evidence for polarization, either in absolute levels of employment or share of the workforce with the exception, in the middle skilled category, of crafts and related occupations. Manufacturing jobs, captured in the Operators and Assembler category (from here on, OA) in fact, expand in both levels and shares. Section 5 uses data on robot stocks to confirm that robot adoption indeed displaces manufacturing jobs in the advanced countries, but in the developing world, they seem to be complementary.

2 Should we expect to see polarization and labor-displacement in developing countries as well?

The way in which off-shoring and automation technologies play out in developing economies may differ from their advanced counterparts for several reasons:

Differing initial occupational distributions: Potential polarization dynamics are layered on very different initial occupational structures and positions in the demographic transition. Most mechanically, in many developing countries the sector of middle income workers engaged in codified tasks is small in the first place- in Ghana, for instance, 90% of the workforce is informal and engaged in low skilled services and artisanal production (see, for example Falco et al. (2015)) and this is representative of many low-income countries. Hence, we would expect to see little in the way of displacement of these types of jobs.

More limited feasibility of automation? The degree to which automation is adopted depends heavily on a country’s technological absorptive capacity, the skill of the workforce, ability
to mobilize resources for large capital investments, capacity for maintenance, and attention to tolerances which may make it less easy to substitute away from labor in many poorer countries. Such factors contribute the the slower rate of technological diffusion, including robot use, in general to developing countries (Comin and Mestieri 2018).

**Recipients of off-shored jobs:** Off-shored jobs from advanced countries are precisely moving to developing countries and hence we would expect to see a complementary expansion of the middle- a “de-polarization” of the wage distribution in at least some host countries. Since multinational assembly operations will often included state of the art plants, including robots, it is possible that we may see a positive comovement of robots and manufacturing employment. That said, to the degree that newer arrivals to off-shoring, such as China or Vietnam, compete with established destinations such as Mexico, the net effect of diversion vs. increased total off-shoring is unclear. Hanson and Robertson (2008) find that for Hungary, Malaysia, Mexico, Pakistan, the Philippines, Poland, Romania, Sri Lanka, Thailand, and Turkey, China’s impact has been negative, but relatively small. Lederman et al. (2009) finds similarly modest effects for Latin America. Hence, the diversion effects, to date, seem muted and we may find overall, that trade generates the reverse of, or at least milder, polarization effects.

3 Data

The Integrated Public Use Microdata Series (IPUMS) developed by the Minnesota Population Center harmonizes census micro-data from around the world. The project has collected the world’s largest archive of publicly available census samples. The data are coded and documented consistently across countries and over time to facilitate comparative research.\(^5\)

*Employment:* We use the *occisco* variable which records the person’s primary occupation.\(^6\)

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\(^5\)See [https://international.ipums.org/international/](https://international.ipums.org/international/).

\(^6\)For someone with more than one job, the primary occupation is typically the one in which the person
coded according to the major categories in the International Standard Classification of Occupations (ISCO) scheme for 1988 and have 11 categories: Legislators, Senior Officials and Managers; Professionals; Technicians and Associated Professionals; Clerks, Service Workers and Shop and Market Sales; Skilled Agricultural and Fishery Workers; Crafts and Related Trades Workers; Plant and Machine Operators and Assemblers (from here on termed OA); Elementary Occupations; Armed Forces and other occupations and no identified occupations. Table A-1 lays out the categories we include in more detail.

Rather than using the occisco variable, Autor (2010) and Autor and Dorn (2013) map these 4-digit categories into a distinct set of skill sets listed in Figure A-1 to better capture “routine” tasks in the US. Hence, in the original ISCO categorization, operators of machines in manufacturing appear in “Plant and Machine Operators, and Assemblers” (category 8) but manufacturing workers who don’t operate machinery appear in “elementary occupations” (category 9). Both may be more routine than, for instance, food preparation or personal care, also found in category 9, which require potentially less skill, but which are also less easy to automate.

Using the occisco variable allow us to work with numerous countries with varying degrees of disaggregation and sometimes inconsistent or ambiguous categorizations across time that IPUMS has standardized into uniform categories. As we show below, for the US, the conclusions under both methodologies does not change appreciably.

The available census data for developing countries for which we can follow employment in a substantive way is small but not unrepresentative. In our final sample, we have information for 80 countries for which we have on average 2.93 census between 1960 and 2015.

Advanced Countries (AC) includes Austria, Canada, France, Germany, Greece, Ireland, Italy, had spent the most time or earned the most money.
Developing Countries (DC) includes Argentina, Armenia, Belarus, Bolivia, Brazil, Burkina Faso, Cambodia, Cameroon, Chile, China, Colombia, Costa Rica, Cuba, Dominican Republic, Ecuador, Egypt, El Salvador, Ethiopia, Fiji, Ghana, Guinea, Haiti, Hungary, India, Indonesia, Iran, Iraq, Jamaica, Jordan, Kenya, Kyrgyz Republic, Liberia, Malawi, Malaysia, Mali, Mexico, Mongolia, Morocco, Mozambique, Nicaragua, Nigeria, Pakistan, Panama, Paraguay, Peru, Philippines, Puerto Rico, Romania, Rwanda, Senegal, Sierra Leone, Slovenia, South Africa, South Sudan, St. Lucia, Sudan, Tanzania, Thailand, Turkey, Uganda, Uruguay, Venezuela, Vietnam, West Bank and Gaza, Vietnam and Zambia.

Robots: Data on robots are collected by the International Federation of Robotics (IFR) whose statistical department is the primary global resource on robot installation. They are collected from nearly all industrial robot suppliers worldwide and supplemented with information from several national robot associations by type, country, industry and application. The industrial robot is defined as an “automatically controlled, re-programmable multipurpose manipulator programmable in three or more axes” and a service robot as one “that performs useful tasks for humans or equipment excluding industrial automation applications.” The service life is estimated at 12 years and hence, assuming immediate withdrawal thereafter, the reported stocks are the sum of installations over that period.

Import Competition: Import competition is the other hypothesized driver of operator displacement in the literature. As a proxy, we employ imports from China as a fraction of domestic output, GDP and imports.

Other controls: All regressions include a time trend to capture other trending unobserved factors over the same period. We further allow for differential trends by also including time interacted with pre-sample (1980s and 1990s) averages of population, openness as measured
by \((X+M)/GDP\) as from World Bank Development Statistics and import competition defined as imports from China as a share of domestic production.

4 Results

4.1 Polarization

Table 1 reports descriptive statistics. Figure 1 presents the mean annual percentage change in employment by category for four countries for which data are very complete: US, France, Mexico and India. To begin, we confirm that neither our data or categorization are leading change the advanced country stylized facts from previous studies. Annex Figure A-1 replicates Autor’s (2015) graph and shows a close correspondence with our US results: OA, and crafts and related show a decline across the last decade compared to the elementary occupations and the more skilled categories. The same appears to be the case for France consistent with the literature arguing this is a common phenomenon across advanced countries.

The next two panels of Figure 1 suggest that the experience in the developing world is far more ambiguous. The OA category in India shows some of the highest growth rates in the sample in both absolute and relative terms and much of the developing country sample (not shown) shows similar trends. For example Vietnam we have only one decade, 1999-2009 to track and hence do not show the graph, but it serves as perhaps the archetypal off-shoring destination that hosts Samsung, Intel and others and shows that OA have increased relative to every category with the exception of professionals. Ecuador, Egypt, El Salvador, Ghana, Malawi, Mali, Morocco, Nicaragua, Peru, South Africa, are all similar.

Mexico (and similarly Brazil, not shown) also show absolute gains in these categories, both quite rapidly up to 2000. However, growth has slowed over the 2000s and relative growth indeed does suggest potential polarization. The literature cited above argues for only modest impact of the emergence of China and India on Latin America. However, it may
be that Brazil and Mexico were more industrialized or have been more integrated in the automation wave than others.

To illustrate these aggregate tendencies, Figure 2 plots the average growth rate by sector post-2000 relative to pre-2000 across our broader sample of countries for both Advanced and Developed Countries after controlling for individual country fixed effects. It is clear that the patterns is very different between the two samples. In the advanced countries, both skilled agricultural and operators show absolute declines while more advanced and elementary tasks increase. In the developing countries, operators, professionals and elementary occupations grow at approximately the same rate.

Tables 2 and 3 confirm these visible trends with the full panel of our countries. Specifically, we estimate the equations:

\[ L_{it} = \beta_1 I[t \geq 2000]_t \times AC_i + \beta_2 I[t \geq 2000]_t \times DC_i + \beta_3 t_{1960} + \gamma_i + \varepsilon_{it} \]  
\[ L_{it} = \alpha_1 I[t \geq 2000]_t + \alpha_2 I[t \geq 2000]_t \times DC_i + \alpha_3 t_{1960} + \gamma_i + \varepsilon_{it} \]

where \( L_{it} \) is the log-level (or the share) of each of the major categories in the International Standard Classification of Occupations (ISCO) scheme for country \( i \) in year \( t \). \( I[.] \) is a dummy variable equals to one if the condition \( [t \geq 2000] \) is satisfied, 0 otherwise; \( \gamma_i \) captures individual country fixed effects. \( t_{1960} \) is a trend starting at 1960. Equation 1 tests whether if the tendencies differ across the two groups of countries after 2000, while equation 2 tests if any differences are statistically significant. The time dummies capture differential changes by job category after the break point between advanced and developing country groups relative to the pre-breakpoint period.\(^{7}\) We report cluster standard errors at the country level (see Bertrand et al. (2004)).

\(^{7}\) Preliminary regressions allowing the break point to change from 1995-2005 suggest 2001 as having the most explanatory power (\( R^2 \)), very close to the break point discussed by Autor (2010) and this informs the definition of the dummies above.
Panel A in Table 2 presents the results for the log of absolute employment as the dependent variable and Panel B, the share of employment, each by category. The presence of country fixed effects means that the dummies are measuring the average of country log level changes in employment (shares) by group relative to their pre-2000 levels and not relative to some third category. These broadly approximate the growth rate of the second period relative to the first.

Several regularities merit note. First, in absolute numbers, the Technicians, Professionals and Legislators categories are growing at similar rates in both the advanced and developing countries. However, as a share of the market, they are growing much faster in the advanced countries.

Second, the OA and Crafts categories in the advanced countries are stagnant, with growth rates insignificantly different from zero. However, in developing countries, these categories are expanding especially OA which is the third fastest growing. As a share of the workforce (panel B) OA is increasing almost as much as professionals. Craft workers are, however, decreasing and that may yield some ambiguity about the trends in the middle segment measured as shares found in WorldBank (2016).

Together, these distinct relative movements of the middle and upper segments of the market in absolutes and shares lead to the polarization found in the advanced countries. However, the expansion of the OA category more or less at pace with the technicians, professionals and legislators and managers category dampens the polarizing dynamic in developing countries.

In the bottom segment, the contribution to polarization is more ambiguous. The advanced countries see rates of growth in, for instance Services and Sales growing relatively quickly Developing countries see average growth for Elementary Occupations and high growth
in Services and Sales that increases shares of the latter importantly. This is partly coun-
terbalanced by a more rapid loss in share by skilled Agricultural and Fishery workers by a
dramatic 11 percent relative to 5 percent in the advanced countries.

Annex tables 2 and 3 estimate equation 2 and explicitly test for differing evolution of
each job category across the advanced and developing country samples by including an in-
teractive variable for developing countries. Table 2 shows these differences to be significant
for employment in Services and Sales, Agriculture and Fishery, Clerks, Crafts and OA, and
in shares for Services, Agriculture and Fisheries, Clerks, OA, Technicians, Professionals and
Legislators and Managers although the last three enter with a negative sign, consistent with
less polarization. Including a time trend in table A-3 does not alter the results. Overall,
there are clear differences in how advanced and developing country markets have evolved.

In sum, in the advanced countries, we do see stagnation in the categories associated
with the displacement of codifiable tasks and in particular in the operators and assemblers
category, mainly relative to the surge in higher end employment. However, in developing
countries, the picture is more ambiguous. In the middle segments, the Crafts segment has
continued to grow, but at rate leading to a relative decline. However, the critical OA cate-
gory continues to grow at rates similar to the professional categories and gains share of the
labor force.

Since the OA category is of such import in the polarization and narrative and policy
debate, and because it behaves so distinctly across advanced and developing countries, the
rest of the paper will focus on the drivers of its evolution over the two sets of countries. Table
3 reestimates equation 2 but with more controls and tests for robustness. Column 1 first
demonstrates no clear pattern globally in the evolution of OA, either in absolute number or
as a share of the workforce. However, columns 2 and 3, including both linear and quadratic
trends, find the interactive indicator for developing countries to be strongly significant and
reveals a very clear divergence between the advanced and developing countries with the former showing a sharp decline by both measures, and the latter showing a sharp increase. Column 4 introduces year dummies which obviate the advanced country terms and again confirms the relatively positive evolution of OA in developing countries. Column 6 allows for distinct trends interacted with the pre-sample averages of population, Chinese competition and the measures of openness which drops the coefficient in both measures by roughly 8 percent. Column 5 confirms that it is the introduction of the controls and not the reduced observations that drive the the reduction in magnitudes.

4.2 Robots

What drives these differences between the experience of developing and advanced countries? Again, the literature highlights trade competition and automation as the prime suspects. In this section we focus primarily on the latter as proxied by the arrival of robots but controlling where possible for increased trade competition as proxied by Chinese import penetration.

The solid line in Figure 3 shows the total global robot stock as aggregated by IFR and documents a dramatic increase in robots over recent decades. There were 3,000 industrial robots installed in 1973, rising to 1,059,000 by 2010 and forecasts are of more than a doubling to 2,589,000 by 2019. Robots are primarily concentrated in the automotive, electrical/electronics, metal and chemical and plastics industries, some of the industries that are precisely shedding labor. The IFR Annual Executive Summary in 2018 notes that 73 percent of robot sales were to five countries, China, Japan, the Republic of Korea, the United States and Germany. However they are present in many more. As an incomplete list: Asia, Thailand, Taiwan, Singapore and India; In Europe, Belgium, Denmark, Hungary, Italy, France, Spain, Turkey, Slovakia, Slovenia, Sweden, Finland, and Romania; in the Western Hemisphere, Mexico, Brazil and Canada. Hence, across both the advanced country and developing country samples there is substantial variation in robot installation.
Information at the country level is available since 1993 and for our core sample, we use the data as tabulated. However, we are also able to expand the sample with the assumptions that 1. before 1965, the global stock of robots was zero so we impute that to all countries; 2. if a country shows zero robots in 1993, we assume that was the case from 1965-1993 and 3. for countries with a strictly positive amount of robots in 1993, a back-cast regressing log (1+robots) on a polynomial of degree five in time offers a reasonable approximation to unobserved values. As a rough test of the reasonableness of these assumptions, Figure 3 plots the aggregate of our imputations and show it tracks the IFR aggregate extremely well except for the brief 1990-91 period.\footnote{See \url{https://ifr.org/img/uploads/Presentation_market_overviewWorld_Robotics_29_9_2016.pdf}; \url{https://ifr.org/downloads/press/02_2016/Executive_Summary_Service_Robots_2016.pdf}}

Figure 4 plots the unconditional relationship between the stock of robots as a share of the workforce and OA as a share of the workforce. For the advanced countries, the relationship is striking downward sloping suggesting substitution and confirms the previous literature. However, for the developing countries, the relationship appears strongly positive with Slovenia, Hungary and Mexico as strong leverage points, although the positive relationship holds up without them.

To explore the robustness of this initial picture, we estimate

\[
L_{it} = \beta_1 Robots_t \times DC_i + \omega_t + \gamma_i + \varepsilon_{it} \tag{3}
\]

\[
L_{it} = \beta_0 Robots_{it} + \beta_2 Robots_{it} \times DC_i + \omega_t + \gamma_i + \varepsilon_{it} \tag{4}
\]

where, again, \(L\) is either the log of operators and assemblers or the share, and robots is the log of the stock.
Equation 3 exploits the evolution of the global stock of robots and Equation 4 country level series. For developing countries we take the stock of world robots as exogenous and effectively ask how the global move towards automation on has affected them. In similar exercises, Autor and Salomons (2018) use national robot stocks as an instrument for TFP, thereby also presuming exogeneity, although Acemoglu and Restrepo (2017) is more circumspect and test for various alternative channels. Unfortunately, our sample does not permit us to instrument, for example, using lags, nor would this obviously be a good solution for such a relatively slow moving process.

Table 4 presents the results of estimating equation 3. Column 1 includes dummies for both advanced and developing countries, letting us isolate the coefficients by sample. It shows that consistent with the previous literature, there has been a strong and significant negative impact in the advanced countries. However, overall we see a strong positive impact in the developing countries, significant at the 10 percent level. Columns 2 and 3, employ only an indicator variable on DCs to test the significance of this difference when linear and quadratic trends are included respectively, and shows that, in fact, the difference between the two samples is strongly significant and of large magnitude leaving the impact of robots in developing countries for both employment and share being positive (1, 2) or weakly negative (3). Columns 4-6 introduce year dummies which, while offering the most flexible form of control for other time varying factors, only permit estimating the differential effect and show again, that effect to be strongly significant.

In Columns 5-6, the sample is given by the countries that have observable information in pre-determined controls (variable trends generated by interacting pre-2000 averages of population, trade openness, and penetration of Chinese imports with a time trend). The inclusion of this new trends reduce the coefficient in less than 5%. Parallel with the employment trends documented above, there is a large negative effect of robots for the advanced countries that is robust to the inclusion of a variety of controls for other trending factors,
that is not shared by the developing world.

Table 5 estimates Equation 4 which exploits individual country variation in robots stocks. The cross country variation also allows us to explicitly test for the impact of trade competition as well. As in table 4, Column 1 establishes a negative significant impact on OA level for the whole global sample, although no significant impact in shares. Column 2 adds the interactive variable for LDCs that, again, allows us to reveal the heterogeneity in the sample: there has been a significant decrease in both number and share of the workforce in operators as a result of national robot adoption in the advanced countries. However, the interactive variable suggests, again, a significant difference with the advanced countries leaving the compound coefficient being positive or close to zero. In column 2, the P values of the total effect suggest that for the level of employment, this effect is not significant although it is for the share at the 10 percent. Column 3 includes the varying trends and preserves the previous results in levels although the negative effect for advanced countries disappears for shares. Further, though the difference between the two samples remains strongly significant, the P value on the compound effect in developing countries is now insignificant.

Column 4 shows no remotely significant impact of trade competition for either sample. The negative effect of robots on the advanced countries remains strong although the interactive effect for the developing countries is now only significant at the 10 percent level for both levels and shares and, again, the P values suggest that the compound effects is insignificantly different from zero. These results hold for whatever normalization of Chinese imports we employ: imports/GDP, imports/population, and imports over total imports.

Column 5 replicates these last two specifications but with the extended (40 percent larger). Again, import competition is not remotely significant. What reemerges is the strong negative effect for the advanced countries and a significant difference with the developing countries. For the latter, in the levels specification, the compound effect is insignificantly
different from zero. However, in the share specification, it is strongly positive and significant at the 10 percent level without the China trade proxy, and the 5 percent level with.

The magnitudes of these effects are large and similar to those of previous studies. As a back of the envelope calculations, Autor (2010) reports that in the US between 1999 and 2009 the number of operators fell from 17,932,881 in 1999 to 13,897,287 in 2009, a fall of approximately 22.5 percent. Across that same period, the IFR reports that the stock of robots grew 105.64 percent, from 79,944 in 1999 to 164,396. The coefficient in column 3 of Table 5 implies a reduction in operators of 11.2 percent or roughly half of the variation of the fall in OA in that period. Repeating the exercise for the previous decade roughly halves the effect. With all relevant caveats, these are of the magnitude found by Dauth et al. (2017) that robots account for almost 23 percent of the overall decline of manufacturing employment in Germany over the period 1994-2014.

A plausible explanation for the positive effect of robots on OA employment found in most specifications for DCs is that off-shoring of modern factories both introduces robots and creates manufacturing jobs where there were none before. The most important leverage points in figure 4 among the DCs are Slovenia (2002), Hungary (2011) and Mexico (2015), all of which are bases for foreign assembly of cars and electronic devices. In a sense, then the positive impact of robots, and the lack of polarization, is importantly driven by outsourcing.

5 Conclusion

This paper has used global census data to explore to what degree findings of polarization in the advanced world can be found in the developing world and how much labor displacement by automation drives these patterns. We confirm previous findings of polarization for the advanced world. However, despite evidence that similar dynamics may be at work in China and Mexico, we find only limited evidence for polarization in developing countries. The key
category- machine operators and assemblers- does not show absolute or relative decrease in most developing countries across the last decades. In fact, they show relatively strong growth leading to an increase in share of employment.

We then explore the causes of these differential effects, focusing on the growth in the use of robots and controlling for the impact of trade, in particular Chinese import penetration. We find little impact of trade competition on either advanced or developing countries. However, robots enter very significantly negatively in the advanced countries, confirming the substitution effect found in the literature. We show this effect can explain a substantial fraction of the loss of manufacturing jobs in the advanced countries and contributes to polarization. However, the developing countries show, again, significantly different behavior from the advanced such that robots penetration appears to be having an insignificant or a positive effect. This is plausibly due to being on the receiving end of off-shoring and, in modern industries, robots.

This arguably positive relationship between automation and assembly related employment does not allow confident extrapolation to the future. The countries with the most dramatic positive co-movement of robots and employment, such as Slovenia, Hungary and Mexico, are those with substantial FDI which brings robot capital to combine with local labor. However, there is evidence of a reduction of exports from Mexico to the US as a result of US automation, and of large displacement effects of local automation in China, and Mexico suggesting that the net effects are not easily predictable over the medium term. The evidence we find in Brazil and Mexico of a relative decline in the operators and assemblers category suggesting latent polarizing forces may be at work and merit monitoring.
References

Acemoglu, D. and Autor, D. (2011). Skills, tasks and technologies: Implications for employment and earnings. *Handbook of labor economics*, 4:1043–1171.

Acemoglu, D., Autor, D., Dorn, D., Hanson, G. H., and Price, B. (2016). Import competition and the great us employment sag of the 2000s. *Journal of Labor Economics*, 34(S1):S141–S198.

Acemoglu, D. and Restrepo, P. (2015). The race between man and machine: Implications of technology for growth, factor shares and employment.

Acemoglu, D. and Restrepo, P. (2017). Robots and jobs: Evidence from us labor markets.

Acemoglu, D. and Restrepo, P. (2019). Automation and new tasks: How technology displaces and reinstates labor.

Artuc, E., Christiaensen, L., and Winkler, H. J. (2019). *Does Automation in Rich Countries Hurt Developing Ones?: Evidence from the US and Mexico*. The World Bank.

Autor, D. and Dorn, D. (2013). The growth of low-skill service jobs and the polarization of the us labor market. *American Economic Review*, 103(5):1553–1597.

Autor, D., Levy, F., and Murnane, R. (2003). The skill content of recent technological change: an empirical exploration. *The Quarterly Journal of Economics*.

Autor, D. and Salomons, A. (2018). Is automation labor-displacing? productivity growth, employment, and the labor share.

Autor, D. H. (2010). The polarization of job opportunities in the us labor market: Implications for employment and earnings. *Center for American Progress and The Hamilton Project*.

Autor, D. H. (2015). Why are there still so many jobs? the history and future of workplace automation. *The Journal of Economic Perspectives*, 29(3):3–30.
Beaudry, P., Green, D., and Sand, B. (2013). The great reversal in the demand for skill and cognitive tasks. *National Bureau of Economic Research, w18901(8)*.

Bertrand, M., Duflo, E., and Mullainathan, S. (2004). How much should we trust differences-in-differences estimates? *Quarterly Journal of Economics, 119*:249–275.

Brynjolfsson, E. and McAfee, A. (2014). *The second machine age: work, progress, and prosperity in a time of brilliant technologies*. WW Norton & Company.

Comin, D. and Mestieri, M. (2018). If technology has arrived everywhere, why has income diverged? *American Economic Journal: Macroeconomics, 10*(3):137–78.

Cortes, G. M. and Morris, D. M. (2019). Are routine jobs moving south? evidence from changes in the occupational structure of employment in the us and mexico.

Dauth, W., Findeisen, S., Südekum, J., and Woessner, N. (2017). German robots—the impact of industrial robots on workers.

David, H., Dorn, D., and Hanson, G. H. (2013). The china syndrome: Local labor market effects of import competition in the united states. *The American Economic Review, 103*(6):2121–2168.

Faber, M. (2018). Robots and reshoring: Evidence from mexican local labor markets. Technical report, Faculty of Business and Economics-University of Basel.

Falco, P., Maloney, W. F., Rijkers, B., and Sarrias, M. (2015). Heterogeneity in subjective wellbeing: An application to occupational allocation in africa. *Journal of Economic Behavior & Organization, 111*:137–153.

Giuntella, O. and Wang, T. (2019). Is an army of robots marching on chinese jobs?

Goos, M., Manning, A., and Salomons, A. (2014). Explaining job polarization: Routine-biased technological change and offshoring. *American Economic Review, 104*(8):2509–26.
Graetz, G. and Michaels, G. (2018). Robots at work. *Review of Economics and Statistics*, 100(5):753–768.

Gregory, T., Salomons, A., and Zierahn, U. (2016). Racing with or against the machine? evidence from europe. *Evidence from Europe (July 15, 2016). ZEW-Centre for European Economic Research Discussion Paper*, (16-053).

Hallward-Driemeir, M. and Nayyar, G. (2019). Have robots grounded the flying geese? evidence from greenfield fdi in manufacturing. Technical report, World Bank.

Hanson, G. H. and Robertson, R. (2008). China and the manufacturing exports of other developing countries. Technical report, National Bureau of Economic Research.

Katz, L. F., Kearney, M. S., et al. (2006). The polarization of the us labor market. *American Economic Review*, 96(2):189–194.

Lederman, D., Olarreaga, M., and Perry, G. (2009). *China’s and India’s challenge to Latin America: opportunity or threat?* World Bank Publications.

WorldBank (2016). *Digital Dividends*. 
Tables and Figures

Figure 1: Changes in Employment by Occupation:

United States

| Occupation                  | 1970–1980 | 1980–1990 | 1990–2000 | 2000–2005 | 2005–2010 |
|-----------------------------|-----------|-----------|-----------|-----------|-----------|
| Legislators and Managers    |           |           |           |           |           |
| Craftsmen and related       |           |           |           |           |           |
| Clerks                      |           |           |           |           |           |
| Elementary occupations      |           |           |           |           |           |
| Professors                  |           |           |           |           |           |
| Operators and assemblers    |           |           |           |           |           |
| Technicians                 |           |           |           |           |           |
| Skilled agricultural and fishery |     |           |           |           |           |
| Service workers             |           |           |           |           |           |
| United States               | −2        | 0         | 2         | 4         | 6         |

France

| Occupation                  | 1968–1975 | 1975–1982 | 1985–1990 | 1990–1999 | 1999–2006 |
|-----------------------------|-----------|-----------|-----------|-----------|-----------|
| Legislators and Managers    |           |           |           |           |           |
| Craftsmen and related       |           |           |           |           |           |
| Clerks                      |           |           |           |           |           |
| Elementary occupations      |           |           |           |           |           |
| Professors                  |           |           |           |           |           |
| Operators and assemblers    |           |           |           |           |           |
| Technicians                 |           |           |           |           |           |
| Skilled agricultural and fishery |     |           |           |           |           |
| Service workers             |           |           |           |           |           |
| France                      | −10       | 0         | 10        | 20        | 30        |

Mexico

| Occupation                  | 1960–1970 | 1970–1990 | 1990–2000 | 2000–2010 |
|-----------------------------|-----------|-----------|-----------|-----------|
| Legislators and Managers    |           |           |           |           |
| Craftsmen and related       |           |           |           |           |
| Clerks                      |           |           |           |           |
| Elementary occupations      |           |           |           |           |
| Professors                  |           |           |           |           |
| Operators and assemblers    |           |           |           |           |
| Technicians                 |           |           |           |           |
| Skilled agricultural and fishery |     |           |           |           |
| Service workers             |           |           |           |           |
| Mexico                      | −5        | 0         | 5         | 10        |

India

| Occupation                  | 1983–1987 | 1987–1993 | 1993–1999 | 1999–2004 |
|-----------------------------|-----------|-----------|-----------|-----------|
| Legislators and Managers    |           |           |           |           |
| Craftsmen and related       |           |           |           |           |
| Clerks                      |           |           |           |           |
| Elementary occupations      |           |           |           |           |
| Professors                  |           |           |           |           |
| Operators and assemblers    |           |           |           |           |
| Technicians                 |           |           |           |           |
| Skilled agricultural and fishery |     |           |           |           |
| Service workers             |           |           |           |           |
| India                       | −2        | 0         | 2         | 4         |

Note: Change in employment in employment categories as described in annex 1.
Figure 2: Changes in Employment by Occupation after 2000, 1960-2015

Note: Change in employment in employment categories as described in annex 1.
Figure 3: Country level aggregates and world robot data

Note: Increase in total global number of robots as reported by International Federation of Robotics (IFR) and aggregated country level series including imputations by authors (Autor 2010)
Figure 4: Robots have differing impacts on employment in advanced vs developing countries, 1979-2009

Note: Robot penetration defined as robots in each country divided by 100,000 workers vs share of assembler and operators in the workforce. Robots as reported by International Federation of Robotics (IFR).
Table 1: Summary statistics

|                  | (1)  | (2)  | (3)  | (4)  | (5)  | (6)  |
|------------------|------|------|------|------|------|------|
|                  | Obs. | Mean | Median | Std. Dev. | Min | Max  |
| **A. Log of employment** |      |      |      |      |      |      |
| Legislators and Managers | 234  | 12.078 | 12.213 | 2.150 | 7.030  | 17.266 |
| Professionals | 234  | 12.715 | 12.618 | 1.848 | 7.779  | 17.387 |
| Technicians | 234  | 12.223 | 12.230 | 2.099 | 6.363  | 17.203 |
| Clerks | 234  | 12.578 | 12.534 | 1.909 | 8.387  | 17.299 |
| Service workers and market sales | 234  | 13.447 | 13.206 | 1.738 | 8.920  | 17.924 |
| Skilled agricultural and fishery | 234  | 13.918 | 13.651 | 2.057 | 9.248  | 19.972 |
| Crafts and related | 234  | 13.567 | 13.486 | 1.717 | 9.284  | 18.129 |
| Operators and assemblers | 234  | 12.725 | 12.557 | 1.894 | 8.485  | 17.240 |
| Elementary occupations | 234  | 13.214 | 13.228 | 1.908 | 6.292  | 18.617 |
| **B. Share of employment** |      |      |      |      |      |      |
| Legislators and Managers | 234  | 4.341 | 3.813 | 3.264 | 0.087  | 13.834 |
| Professionals | 234  | 6.935 | 6.600 | 4.265 | 0.167  | 21.780 |
| Technicians | 234  | 5.555 | 4.084 | 4.839 | 0.021  | 22.036 |
| Clerks | 234  | 6.816 | 5.935 | 5.022 | 0.148  | 23.335 |
| Service workers and market sales | 234  | 12.664 | 12.634 | 5.696 | 1.550  | 27.397 |
| Skilled agricultural and fishery | 234  | 29.448 | 20.038 | 25.348 | 1.153  | 92.537 |
| Crafts and related | 234  | 14.007 | 14.111 | 5.754 | 1.972  | 29.250 |
| Operators and assemblers | 234  | 7.060 | 6.684 | 5.335 | 0.369  | 35.811 |
| Elementary occupations | 234  | 13.174 | 10.243 | 9.786 | 0.016  | 47.316 |
| **C. Other variables** |      |      |      |      |      |      |
| World robots | 234  | 11.670 | 13.284 | 3.380 | 0.000  | 14.305 |
| Year > 2000 | 234  | 0.410 | 0.000 | 0.493 | 0.000  | 1.000 |
| DC | 234  | 0.778 | 1.000 | 0.417 | 0.000  | 1.000 |
| Robots | 138  | 3.276 | 1.242 | 3.759 | 0.000  | 12.046 |
| China imports | 138  | 0.000 | 0.000 | 0.000 | 0.000  | 12.046 |
| Robots (all sample) | 234  | 1.932 | 0.000 | 3.304 | 0.000  | 12.046 |
| China imports (all sample) | 234  | 0.000 | 0.000 | 0.000 | 0.000  | 0.002 |

Note: Employment data from IPUMS censuses. Categorization as in Annex 1. Log Robots as reported by International Federation of Robotics (IFR). China imports = import penetration as a share of domestic production.
Table 2: Changes on employment and employment share by category after 2000
Advanced and Developing countries

|                  | (1)  | (2)  | (3)  | (4)  | (5)  | (6)  | (7)  | (8)  | (9)  |
|------------------|------|------|------|------|------|------|------|------|------|
|                  |      |      |      |      |      |      |      |      |      |
| Elementary       |      |      |      |      |      |      |      |      |      |
| occupations      |      |      |      |      |      |      |      |      |      |
| Service          |      |      |      |      |      |      |      |      |      |
| and sales        |      |      |      |      |      |      |      |      |      |
| Skilled          |      |      |      |      |      |      |      |      |      |
| agricultural     |      |      |      |      |      |      |      |      |      |
| and fishery      |      |      |      |      |      |      |      |      |      |
| related          |      |      |      |      |      |      |      |      |      |
| Clerks           |      |      |      |      |      |      |      |      |      |
| Crafts           |      |      |      |      |      |      |      |      |      |
| and assemblers   |      |      |      |      |      |      |      |      |      |
| Professionals    |      |      |      |      |      |      |      |      |      |
| Managers         |      |      |      |      |      |      |      |      |      |
| Legislators      |      |      |      |      |      |      |      |      |      |

Panel A. Dependent variable is the log of employment by category according the column

|                  | (1)  | (2)  | (3)  | (4)  | (5)  | (6)  | (7)  | (8)  | (9)  |
|------------------|------|------|------|------|------|------|------|------|------|
| Year ≥ 2000 × AC| 0.217| 0.417***| -0.482***| 0.198**| 0.110| -0.158| 1.103***| 0.721***| 0.629***|
|                  | (0.265)| (0.102)| (0.121)| (0.0763)| (0.129)| (0.270)| (0.148)| (0.0725)| (0.154)|
| Year ≥ 2000 × DC| 0.623***| 1.001***| 0.0242| 0.575***| 0.427***| 0.764***| 1.261***| 0.829***| 0.633***|
|                  | (0.136)| (0.0868)| (0.0628)| (0.0871)| (0.0751)| (0.0994)| (0.169)| (0.0758)| (0.111)|

Panel B. Dependent variable is the share of employment by category according the column

|                  | (1)  | (2)  | (3)  | (4)  | (5)  | (6)  | (7)  | (8)  | (9)  |
|------------------|------|------|------|------|------|------|------|------|------|
| Year ≥ 2000 × AC| -1.289| 2.118*| -5.085***| -0.853| -2.916**| -5.453| 6.366***| 4.771***| 2.341***|
|                  | (1.959)| (1.208)| (1.015)| (0.676)| (1.422)| (3.400)| (0.664)| (0.694)| (0.803)|
| Year ≥ 2000 × DC| 0.896| 5.412***| -11.02***| 0.404| -1.214**| 1.308***| 2.312***| 1.587***| 0.314|
|                  | (1.054)| (0.808)| (1.850)| (0.245)| (0.596)| (0.394)| (0.427)| (0.282)| (0.253)|

|                  | (1)  | (2)  | (3)  | (4)  | (5)  | (6)  | (7)  | (8)  | (9)  |
|------------------|------|------|------|------|------|------|------|------|------|
| Observations     | 234  | 234  | 234  | 234  | 234  | 234  | 234  | 234  | 234  |
| Countries        | 80   | 80   | 80   | 80   | 80   | 80   | 80   | 80   | 80   |

Notes: Regression results of equation 2 showing changes in employment growth by category after 2000. Dependent variable panel A=log employment by employment category; panel B= share of category in total employment. Categories as defined in Annex 1. AC, DC are indicator variables for Advanced and Developing Countries respectively. All regressions include country fixed effects. Regression of log employment on dummy for post-1990 period by sector with country fixed effects. Advanced Countries (AC) and Developing Countries (DC) samples as defined in text. IPUMS data. Cluster standard errors at country level. *** p < 0.01, ** p < 0.05, * p < 0.1.
Table 3: Testing differential employment evolution effects of operators and assemblers employment after 2000
Advanced countries vs Developing countries

|                | (1)     | (2)     | (3)     | (4)     | (5)     | (6)     |
|----------------|---------|---------|---------|---------|---------|---------|
| **Panel A:**   |         |         |         |         |         |         |
| Dependent      |         |         |         |         |         |         |
| variable       |         |         |         |         |         |         |
| is the log of  |         |         |         |         |         |         |
| operators and  |         |         |         |         |         |         |
| assemblers     |         |         |         |         |         |         |
| **Year ≥ 2000**| 0.00170 | -0.799***| -0.740***|         |         |         |
|                | (0.0822)| (0.238) | (0.227) |         |         |         |
| **Year ≥ 2000 × DC** | 0.997***| 0.993***| 0.982***| 0.989***| 0.899***|         |
|                | (0.302) | (0.301) | (0.238) | (0.242) | (0.218) |         |
| **Panel B:**   |         |         |         |         |         |         |
| Dependent      |         |         |         |         |         |         |
| variable       |         |         |         |         |         |         |
| is the share   |         |         |         |         |         |         |
| of operators  |         |         |         |         |         |         |
| and assemblers |         |         |         |         |         |         |
| **Year ≥ 2000**| 0.376   | -5.013**| -4.090**|         |         |         |
|                | (0.697) | (2.338) | (1.983) |         |         |         |
| **Year ≥ 2000 × DC** | 6.709** | 6.641** | 6.500** | 6.568** | 5.618** |         |
|                | (3.275) | (3.237) | (2.610) | (2.651) | (2.207) |         |

|                  | ✓       | ✓       | ✓       | ✓       | ✓       | ✓       |
|------------------|---------|---------|---------|---------|---------|---------|
| Country fixed    |         |         |         |         |         |         |
| effects          | ✓       | ✓       | ✓       | ✓       | ✓       | ✓       |
| Linear trend     | ✓       | ✓       | ✓       |         |         |         |
| Quadratic trend  |         |         |         | ✓       |         |         |
| Year fixed       |         |         |         | ✓       | ✓       | ✓       |
| effects          |         |         |         |         |         |         |
| Controls         |         |         |         |         | ✓       | ✓       |
| Observations     | 234     | 234     | 234     | 234     | 227     | 227     |
| Countries        | 80      | 80      | 80      | 80      | 76      | 76      |

Notes: Regression results of equation 2 showing changes in employment growth for operators and assemblers after 2000, Dependent variable panel A=log employment; panel B= share of category in total employment. AC, DC are indicator variables for Advanced and Developing Countries respectively. All regressions include country fixed effects. Regression of log employment on dummy for post-1990 period by sector with country fixed effects. Advanced Countries (AC) and Developing Countries (DC) samples as defined in text. IPUMS data. Cluster standard errors at country level. Controls are variable trends generated by interacting pre-2000 averages of population, trade openness, and penetration of Chinese imports with time. *** \( p < 0.01 \), ** \( p < 0.05 \), * \( p < 0.1 \).
Table 4: World robots production
Advanced countries vs Developing countries

|                | (1)    | (2)    | (3)    | (4)    | (5)    | (6)    |
|----------------|--------|--------|--------|--------|--------|--------|
| World robots   |        |        |        |        |        |        |
| World robots × AC | -0.112*** |        |        |        |        |        |
|                 | (0.0251) |        |        |        |        |        |
| World robots   | -0.112*** | -0.182*** |        |        |        |        |
|                 | (0.0251) | (0.0505) |        |        |        |        |
| World robots × DC | 0.0532* | 0.165*** | 0.165*** | 0.148*** | 0.147*** | 0.140*** |
|                 | (0.0274) | (0.0302) | (0.0287) | (0.0169) | (0.0167) | (0.0223) |

Panel A: Dependent variable is the log of operators and assemblers

Panel B: Dependent variable is the share of operators and assemblers

|                | (1)    | (2)    | (3)    | (4)    | (5)    | (6)    |
|----------------|--------|--------|--------|--------|--------|--------|
| World robots   |        |        |        |        |        |        |
| World robots × AC | -0.798*** |        |        |        |        |        |
|                 | (0.233) |        |        |        |        |        |
| World robots   | -0.798*** | -1.239*** |        |        |        |        |
|                 | (0.233) | (0.313) |        |        |        |        |
| World robots × DC | 0.442* | 1.240*** | 1.239*** | 1.044*** | 1.039*** | 0.902*** |
|                 | (0.231) | (0.404) | (0.394) | (0.185) | (0.183) | (0.167) |

Country fixed effects ✓ ✓ ✓ ✓ ✓ ✓
Linear trend ✓ ✓ ✓ ✓
Quadratic trend ✓
Year fixed effects ✓ ✓ ✓ ✓
Other controls ✓
Observations 234 234 234 234 227 227
Countries 80 80 80 80 76 76

Notes: Regression results of equation showing changes in operator and assembler employment growth y after 2000 against global robot stock., Dependent variable panel A=log employment; panel B= share of category in total employment. AC, DC are indicator variables for Advanced and Developing Countries respectively as defined in text using IPUMS data. Robots=log global robots stock as tabulated by IRF. Clustered standard errors at country level. Controls are variable trends generated by interacting pre-2000 averages of population, trade openness, and penetration of Chinese imports with time. *** p < 0.01, ** p < 0.05, * p < 0.1.
Table 5: Effects of robots in operation by country on operator and assembler employment in advanced and developing countries

|                      | (1)  | (2)  | (3)  | (4)  | (5)  | (6)  |
|----------------------|------|------|------|------|------|------|
|                      | Core sample | Extended sample |
| **Panel A:** Dependent variable is the log of operators and assemblers | | |
| Robots               | -0.0718** (0.0305) | -0.113*** (0.0349) | -0.106*** (0.0382) | -0.106** (0.0412) | -0.131*** (0.0342) | -0.128*** (0.0379) |
| Robots × LDC         | 0.133*** (0.0383) | 0.115** (0.0424) | 0.114* (0.0640) | 0.132*** (0.0321) | 0.122*** (0.0392) | |
| China imports        | 0.0974 (0.293) | | 0.0165 (0.296) | | | |
| China imports × LDC  | -0.0219 (0.278) | | 0.0277 (0.283) | | | |
| *Pvalue* Total effect | Robots × LDC | 0.578 | 0.790 | 0.863 | 0.987 | 0.844 |

**Panel B:** Dependent variable is the share of operators and assemblers

|                      | (1)  | (2)  | (3)  | (4)  | (5)  | (6)  |
|----------------------|------|------|------|------|------|------|
|                      | Core sample | Extended sample |
| Robots               | -0.253 (0.296) | -0.538* (0.310) | -0.413 (0.297) | -0.454 (0.355) | -0.626** (0.240) | -0.732** (0.278) |
| Robots × LDC         | 0.922*** (0.287) | 0.728*** (0.233) | 0.801* (0.435) | 1.065*** (0.271) | 1.203*** (0.316) | |
| China imports        | 0.885 (2.246) | | 1.504 (1.753) | | | |
| China imports × LDC  | -0.527 (2.141) | | -1.197 | | | |
| *Pvalue* Total effect | Robots × LDC | 0.0865 | 0.146 | 0.212 | 0.0717 | 0.0448 |

| Country fixed effects | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year fixed effects    | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Pre-Controls          | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations          | 137 | 137 | 137 | 137 | 231 | 231 |
|                       | 38 | 38 | 38 | 38 | 76 | 76 |

**Notes:** Regression results of equation 4 showing change in operator and assembler employment growth from IPUMS after 2000 against log of country robot stock. Dependent variable panel A=log employment; panel B= share of O and A in total employment. AC, DC are indicator variables for Advanced and Developing Countries respectively as defined in text using IPUMS data. Robots=log country level robot stock as tabulated by IRF. Extended sample generated as described in text. Clustered standard errors at country level. Controls are variable trends generated by interacting pre-2000 averages of population, trade openness, and penetration of Chinese imports with time. *** p < 0.01, ** p < 0.05, * p < 0.1.
A Annex:

Figure A-1: Percent Change in Employment by Occupation, 1979-2009

Note: Autor 2010
Table A-1: ISCO categories and mainly subdivisions

| ISCO categories                  | ISCO code | Subdivision                                                                 |
|----------------------------------|-----------|-----------------------------------------------------------------------------|
| Managers                         | 11        | Chief executives, senior officials and legislators                           |
|                                  | 12        | Administrative and commercial managers                                       |
|                                  | 13        | Production and specialised services managers                                 |
|                                  | 14        | Hospitality, retail and other services managers                              |
| Professionals                    | 21        | Science and engineering professionals                                        |
|                                  | 22        | Health professionals                                                         |
|                                  | 23        | Teaching professionals                                                       |
|                                  | 24        | Business and administration professionals                                     |
|                                  | 25        | Information and communications technology professionals                       |
|                                  | 26        | Legal, social and cultural professionals                                     |
| Technicians and associate        | 31        | Science and engineering associate professionals                              |
| associate professionals          | 32        | Health associate professionals                                                |
|                                  | 33        | Business and administration associate professionals                          |
|                                  | 34        | Legal, social, cultural and related associate professionals                  |
|                                  | 35        | Information and communications technicians                                   |
| Clerical support workers         | 41        | General and keyboard clerks                                                  |
|                                  | 42        | Customer services clerks                                                     |
|                                  | 43        | Numerical and material recording clerks                                       |
|                                  | 44        | Other clerical support workers                                               |
| Service and sales workers        | 51        | Personal service workers                                                     |
|                                  | 52        | Sales workers                                                                |
|                                  | 53        | Personal care workers                                                         |
|                                  | 54        | Protective services workers                                                   |
| Skilled agricultural, forestry   | 61        | Market-oriented skilled agricultural workers                                 |
| and fishery workers              | 62        | Market-oriented skilled forestry, fishery and hunting workers                 |
|                                  | 63        | Subsistence farmers, fishers, hunters and gatherers                          |
| Craft and related trades workers  | 71        | Building and related trades workers, excluding electricians                  |
|                                  | 72        | Metal, machinery and related trades workers                                  |
|                                  | 73        | Handicraft and printing workers                                              |
|                                  | 74        | Electrical and electronic trades workers                                      |
|                                  | 75        | Food processing, wood working, garment and other craft                       |
| Plant and machine operators, and | 81        | Stationary plant and machine operators                                       |
| assemblers                       | 82        | Assemblers                                                                   |
|                                  | 83        | Drivers and mobile plant operators                                           |
| Elementary occupations          | 91        | Cleaners and helpers                                                         |
|                                  | 92        | Agricultural, forestry and fishery labourers                                 |
|                                  | 93        | Labourers in mining, construction, manufacturing and transport               |
|                                  | 94        | Food preparation assistants                                                  |
|                                  | 95        | Street and related sales and service workers                                 |
|                                  | 96        | Refuse workers and other elementary workers                                  |
Table A-2: Testing differences in AC/DC employment growth changes after 2000

|                | (1)     | (2)     | (3)     | (4)     | (5)     | (6)     | (7)     | (8)     | (9)     |
|----------------|---------|---------|---------|---------|---------|---------|---------|---------|---------|
|                | Elementary occupations | Service and agricultural Clerks | Skilled operators and assemblers | Crafts and related Managers | Legislators |
| Year ≥ 2000    | 0.217   | 0.417*** | -0.482*** | 0.198** | 0.110   | -0.158  | 1.103*** | 0.721*** | 0.629*** |
|                | (0.265) | (0.102) | (0.121) | (0.0763) | (0.129) | (0.270) | (0.148) | (0.0725) | (0.154) |
| Year ≥ 2000 × DC| 0.406   | 0.584*** | 0.506*** | 0.377*** | 0.317** | 0.922*** | 0.158   | 0.108   | 0.00409 |
|                | (0.298) | (0.134) | (0.136) | (0.116) | (0.149) | (0.287) | (0.225) | (0.105) | (0.190) |

Panel A. Dependent variable is the log of employment by category according the column

Panel B. Dependent variable is the share of employment by category according the column

|                | (1)     | (2)     | (3)     | (4)     | (5)     | (6)     | (7)     | (8)     | (9)     |
|----------------|---------|---------|---------|---------|---------|---------|---------|---------|---------|
| Year ≥ 2000    | -1.289  | 2.118*  | -5.085*** | -0.853 | -2.916** | -5.453  | 6.366*** | 4.771*** | 2.341*** |
|                | (1.959) | (1.208) | (1.015) | (0.676) | (1.422) | (3.400) | (0.664) | (0.694) | (0.803) |
| Year ≥ 2000 × DC| 2.186   | 3.295** | -5.935*** | 1.257* | 1.701   | 6.761*  | -4.054*** | -3.184*** | -2.027** |
|                | (2.224) | (1.454) | (2.110) | (0.719) | (1.542) | (3.423) | (0.789) | (0.749) | (0.842) |

Observations | 234 | 234 | 234 | 234 | 234 | 234 | 234 | 234 | 234 |
Countries     | 80  | 80  | 80  | 80  | 80  | 80  | 80  | 80  | 80  |

Notes: Follows equation 2 but without time trend. Regression results of equation 2 showing changes in employment growth by category after 2000, Dependent variable panel A=log employment by employment category; panel B= share of category in total employment. Categories as defined in Annex 1. AC, DC are indicator variables for Advanced and Developing Countries respectively. All regressions include country fixed effects. Regression of log employment on dummy for post-1990 period by sector with country fixed effects. Advanced Countries (AC) and Developing Countries (DC) samples as defined in text. IPUMS data. Cluster standard errors at country level. *** p < 0.01, ** p < 0.05, * p < 0.1.
Table A-3: Testing differences in AC/DC employment growth changes after 2000, no trend

|                                | (1)       | (2)       | (3)       | (4)       | (5)       | (6)       | (7)       | (8)       | (9)       |
|--------------------------------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|
|                                | Elementary occupations | Service and sales | Skilled agricultural and fishery | Clerks | Crafts and related | Operators and assemblers | Technicians | Professionals | Legislators and Managers |
| Year ≥ 2000                    | -0.633**  | -0.373*** | -0.460*** | -0.568*** | -0.406*** | -0.799*** | -0.329    | -0.181*   | -0.224    |
|                               | (0.282)   | (0.124)   | (0.147)   | (0.114)   | (0.128)   | (0.238)   | (0.217)   | (0.108)   | (0.229)   |
| Year ≥ 2000 × DC              | 0.505*    | 0.677***  | 0.503***  | 0.467***  | 0.377***  | 0.997***  | 0.326     | 0.213**   | 0.104     |
|                               | (0.279)   | (0.131)   | (0.138)   | (0.0973)  | (0.127)   | (0.302)   | (0.246)   | (0.0947)  | (0.198)   |

Panel A. Dependent variable is the log of employment by category according the column

|                                | (1)       | (2)       | (3)       | (4)       | (5)       | (6)       | (7)       | (8)       | (9)       |
|--------------------------------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|
|                                | -2.896    | -0.944    | 6.712**   | -2.388*** | -2.194*   | -5.013**  | 3.149***  | 2.214***  | 1.360     |
|                               | (2.070)   | (1.343)   | (2.581)   | (0.640)   | (1.251)   | (2.338)   | (0.876)   | (0.636)   | (0.867)   |
| Year ≥ 2000 × DC              | 2.374     | 3.653**   | -7.316*** | 1.436**   | 1.617     | 6.709**   | -3.677*** | -2.885*** | -1.912**  |
|                               | (2.203)   | (1.463)   | (2.341)   | (0.663)   | (1.544)   | (3.275)   | (0.888)   | (0.695)   | (0.844)   |

Panel B. Dependent variable is the share of employment by category according the column

|                                | (1)       | (2)       | (3)       | (4)       | (5)       | (6)       | (7)       | (8)       | (9)       |
|--------------------------------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|
|                                | Observations | 234     | 234     | 234     | 234     | 234     | 234     | 234     | 234     |
| Countries                      | 80        | 80        | 80        | 80        | 80        | 80        | 80        | 80        | 80        |

Notes: Follows equation 2 but it does not include a time trend. Regression results of equation 2 showing changes in employment growth by category after 2000, Dependent variable panel A=log employment by employment category; panel B= share of category in total employment. Categories as defined in Annex 1. AC, DC are indicator variables for Advanced and Developing Countries respectively. All regressions include country fixed effects. Regression of log employment on dummy for post-1990 period by sector with country fixed effects. Advanced Countries (AC) and Developing Countries (DC) samples as defined in text. IPUMS data. Cluster standard errors at country level. *** p < 0.01, ** p < 0.05, * p < 0.1.