# Trade, Robots and Automation: The Impact of US Robots on Labor Outcomes in Developing Countries *

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**Abstract**

There is a heated debate about the negative consequences of automation and rapid technological progress on jobs performed by human labor and its implications on the future of manufacturing. While different studies have analyzed the impact of automation in advanced economies, there is scarce evidence for developing ones. The question whether manufacturing is still a sensible and feasible development strategy is critical in creating global equitable and efficient markets. And, studies in low-middle income countries have only examined patterns of job polarization or the direct impact of technology adoption. We explore a new channel on how technology adoption in advanced economies may affect labor outcomes in developing ones: The displacement of traditional economic sectors by the adoption of computer-assisted technologies and robots in advanced countries. We start showing three facts: 1) there is a positive correlation between trade flows and robots; 2) robots adopted by advanced countries are in sectors with traditional comparative disadvantage; 3) preliminary results suggest a negative association between US robot adoption and net exports stemming from developing countries and a negative impact on labor outcomes.

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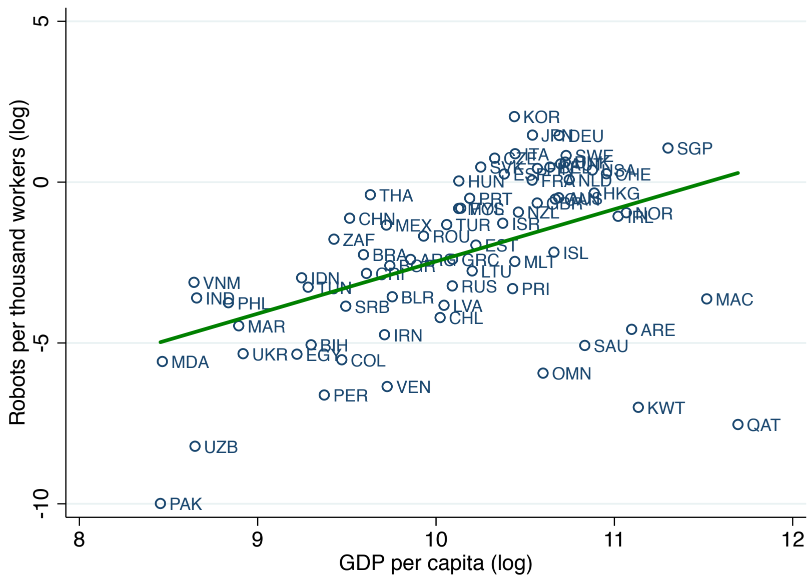
# 1 Introduction

There is a huge and heated debate about the negative consequences of automation and rapid technological progress on jobs performed by human labor. The questions on how susceptible are jobs to computerization and whether technology advances would make labor redundant have received more attention in the last years. Nowadays, the future of jobs has become a priority in the agenda of policymakers, the academic community and the press in several countries. However, most of this debate has taken part in advanced economies such as the United Kingdom or the United States, and there is very little evidence on the negative consequences of robots and computerization on labor outcomes in developing countries.[1] One possible explanation of this lack of evidence is low technology adoption patterns in developing countries.

For instance, figure 1 shows the relationship between robot adoption per thousand workers and GDP per capita. We can observe from the figure that advanced economies are the ones adopting robots instead of low-income countries. In principle, this fact would imply that the negative consequences of automation would not be observed in developing countries since automation patterns so far are low. However, this study argues that we should consider another mechanism on how robot adoption in advanced economies may affect labor outcomes in developing countries: trade between countries.

Figure 1: Robots per thousand workers vs GDP per capita




In particular, our goal is to study whether technology adoption in advanced economies affects labor outcomes in less advanced countries. We hypothesize that the adoption of computer-

[1] There is a descriptive analysis of job polarization in developing countries by (Maloney and Molina, 2016).

assisted technologies and robots in high-income countries displace traditional exports stemming from low-income countries with important implications on local labor outcomes. The general idea consists that robot adoption in the US and other high-income countries has generated a change in comparative advantages across countries. For example, if Mexico used to have a comparative advantage in producing textiles relative to high-income countries, robot adoption in these countries has switched those comparative advantage patterns. By a Hecksher-Ohlin argument, the abundant factors of production in low-income countries (e.g., low skilled workers) are hurt by these new technologies.

In this paper we show some evidence on this mechanism and explore some of the implications on labor outcomes in developing countries using Mexico as a case study. To test our main hypothesis, we use trade flows information provided by BACI; the census samples from IPUMS; and the number of robots adopted in the US, Mexico, and other countries from the International Federation of Robotics (IFR). The IFR provides information by country and industry on the number of robots adopted in recent years.[2] We construct labor market outcomes and measures of exposure to net exports and robots for Mexican municipalities using the data from IPUMS. We make a significant contribution since our work proposes a new indirect mechanism on how labor outcomes in less advanced economies are affected by technology adoption in rich countries.

In the first part, we explore our main hypothesis correlating trade flows and robots at the country-sector cell. For instance, we estimate a gravity equation relating trade flows and robots. We find that there is a positive correlation between trade flows and robots. In particular, countries, and sectors that adopt more robots, export more to the entire world. In the second part, we test the hypothesis that advanced economies are adopting robots in sectors in which they have had a traditionally comparative disadvantage, we estimate an OLS regression relating changes in robots at the country-sector cell to trade deficits in previous periods finding a negative correlation. This result suggests that countries are adopting robots in sectors in which they have had a comparative disadvantage, or in other words, in sectors in which they were exporting less relative to their imports.

Finally, in the last part, we use Mexico as a case study and relate Mexican labor outcomes to net exports, and net export to robot adoption in the US. In our main specification, we exploit variation of the industry composition by region. Our empirical strategy follows directly the work by Acemoglu and Restrepo (2017) and Autor et al. (2013) for the case of robot adoption and Chinese imports in the US. We construct similar Bartik shocks at the industry-region level for Mexican municipalities. Overall, a region in Mexico is more exposed to changes in net exports, and robots adoption in the US, if it has traditionally employed more labor in the sectors affected.

[2]This is the same dataset that (Acemoglu and Restrepo, 2017) used to explore the negative consequences of automation on local employment and wages in the US at the Commuting Zone level.

We run a first stage in which we relate net exports from Mexico to the US with robots in the US economy, and a second stage in which we relate labor outcomes: employment to population ratio, and average earned income to net exports. Our exclusion restriction implies that robots in the US only affect labor outcomes in Mexico through the trade channel.[3] The coefficient of the first stage captures the impact of robot adoption on trade flows stemming from Mexico to the US, while the coefficient of the second stage corresponds to the effect of net exports on local labor market outcomes.

Our main findings suggest a negative association between net exports stemming from Mexico and robots adopted in the US, implying that robots in the US have had some consequences on exports from Mexico. On the other hand, in the second stage, we find a positive correlation between Mexican labor outcomes and net exports, implying that robots in the US generate some negative consequences on labor outcomes in developing countries through our mechanism in the reduced form estimates. For example, one robot adopted per thousand workers in the US decreases net exports from Mexico in 0.19 thousand dollars, and an increase in net exports of ten thousand dollars increases the employment share in 1.3 percentage points and average earnings in 0.2% across Mexican regions.

We proceed to disentangle this effect between low-skilled and high-skilled workers. We find that robots in the US hurt more low-skilled than high skilled workers suggesting that the more abundant factor is the one that loses more from robot adoption. For instance, while there is no effect for high-skilled workers on average earnings, there is a negative association with robots in the U.S and earnings for low skilled workers.

With these three empirical facts at hand, we develop a multisector-multicountry trade model based on the classical framework by Armington and Acemoglu and Restrepo (2017).[4] to improve our understanding of the main mechanisms. In our model, countries produce different varieties within each sector that trade to all countries, there is an iceberg trade cost, and the production function for each variety is a CES good of two composite inputs: high skilled and low skilled. Each composite input takes a CES form and is produced using a continuum of tasks, each task can be produced using labor or robots, which is an endogenous decision of the firm. There is a frontier technology on the tasks, then all tasks beyond this frontier need to be produced with labor instead of robots. We do some comparative statics changing this parameter.

Our model rationalizes different empirical facts, for example, advanced economies adopt more robots than developing countries, and robot adoption has a positive impact on trade flows, especially for sectors in which countries have a comparative disadvantage. Therefore, so far, the model

[3]Due to endogeneity concerns and the fact that robots in the US may have a direct impact on Mexican labor outcomes, we also instrument net exports to the US with robot adoption in other advanced economies as well. This is the identification strategy used by Autor et al. (2013) and Acemoglu and Restrepo (2017).

[4]This part of the paper is still incomplete.

is in line with our empirical findings. In the next steps we want to take the model to the data more seriously.

The rest of this document is organized as follows, section 2 presents a literature review on job polarization and the negative consequences of robot adoption on jobs in both developing and developed countries. Section 3 describes the three sources of data and our main empirical specification, it explains the variation that we are exploiting across Mexican local labor markets to identify the impact of robots on labor outcomes. Section 4 discusses our main results, section 5 concludes, and finally, in the appendix we propose a trade model that can improve our understanding on the main mechanisms at play.

## 2 Literature Review

In this section we review the literature that has studied the impact of automation and robot adoption on different labor outcomes in both advanced and developing economies. We divide this section in two parts. First, the literature that explores job polarization patterns and how automation shape the distribution of skills and occupation in both advanced and developing economies. And second, the literature that has documented the impact of automation on aggregate levels of employment and wages. It is natural that both literatures are related.

### 2.1 Job Polarization

In the case of developed economies several papers have documented the effect of technology adoption on job displacement, job polarization and relative wages across different groups of workers. The classic studies by Autor et al. (1998), and Autor et al. (2002, 2003), provide an explanation on how computerization alters job skills demand and relative wages between skilled and unskilled workers in the US based on job polarization of tasks and routines within occupations. The main implications of these studies is that computerization is associated with reduced labor input of routine tasks and increased labor input for non-routine manual and cognitive tasks decreasing the relative demand of middle skilled workers favouring low and high skilled workers. When the authors translate task shifts on job skill demand, they find that a significant percent of the increase in relative demand favouring college labor in the late 20th century is explained by shifts from routine to non-routine tasks.

Job polarization in developed countries is studied in more detail by Goos and Manning (2007), Goos et al. (2014), and Autor and Dorn (2013). The former paper argues that "routine-biased technological change" is consistent with job polarization in the US. The authors show that between 1975 to 1999 there was a rise in relative share of employment for occupations that are intensive in nonroutine tasks. This rise was concentrated in the upper and the lower part of the empirical distribution of wages contributing to job polarization. Similarly, Goos et al. (2014) analyze the pervasiveness of job polarization in 16 Western European countries, the authors find that recent technological change is biased toward replacing labor in routine tasks. Similarly, they show that task off-shoring to the developing world also decreases the demand for middling relative to high and low skilled occupations increasing job polarization. In the last part of the paper, the authors makes a second contribution developing and estimating a model to quantify the importance of automation vs off-shoring in explaining job polarization. They find that automation is much more important than off-shoring in explaining these patterns in the advance world.

Finally, Autor and Dorn (2013) test the broader hypothesis that polarization is driven by the interaction of consumer preferences in favoring variety over specialization and "routinization". Using a spatial equilibrium model of local labor markets, they add to the conclusions by Autor et al. (2003) preciser descriptions of reallocation of low-skill labor into nonroutine manual tasks. Finally, Autor & Price (2013) document changes in labor input in five task categories -routine cognitive, routine manual, nonroutine analytic, nonrotuine interactive, and nonroutine manual- over a five decade span. This paper shows that employment opportunities were more bended towards workers and occupations that perform relatively less-routine tasks relating, the authors relate the patterns found to technology adoption.

For the case of developing countries Maloney and Molina (2016) use census data to explore to what extent job polarization in advanced economies can also be found in the developing world. First, the authors offer several reasons why we shouldn't expect the same tendencies of job polarization developing countries. Some of the reasons mentioned are: different initial occupational distribution, complementary expansion of the wage distribution due to the net impact of off-shored jobs, removal of barriers to entry, and more limited feasibility of automation. The authors test for structural changes after 2000 using shares of different occupational categories from ISCO. The main finding of this study is that there is not strong evidence of job polarization in developing countries. However, countries such as Indonesia, Brazil and Mexico show a relative decline in the operators category which could suggest potential job polarization in the future.

The previous paper complements other studies focusing on job polarization in the developing world. For example, Goos et al. (2014) and a report from the World Bank (2016) argue that occupations in the middle part of the skill distribution in routine cognitive and manual tasks have decreased relative to high and low skill tasks in developing countries except for a group of countries that includes China, Ethiopia, Argentina and Nicaragua. Our project complements this literature focusing in a particular channel on how automation in advanced economies may affect labor outcomes in developing ones.

Finally, there is also a new literature that explores which jobs are at a higher risk of automation. The classic study by Frey et al. (2013) uses a Gaussian process classifier to estimate the probability of computerisation for 702 detailed occupations. According to their estimates 47% of total US employment is at risk of automation. Moreover, the authors show that there is a negative association between the probability of computerisation and wages, and educational attainment. In other words, the authors find a positive relationship between technology adoption and the skill premium.

### 2.2 Impact of Automation on Employment and Wages

In the second part of this section we focus on the impact of automation on wages and employment instead of job polarization. Acemoglu and Restrepo (2016) develop a task model to study the long run consequences of the "race" between men and technology. The authors focus in two important concerns of accelerated automation: Whether new technologies will make labor redundant; and the recent declines in the share of labor in national income in advanced countries (Autor et al., 2017).

The paper characterizes an equilibrium of tasks when capital is fixed, in this version of their model automation reduces employment and the labor share in national income. However, when the authors endogenize capital accumulation, they find that under reasonable assumptions an increase in automation reduces the cost of producing using labor discouraging further automation and a faster creation of new complext tasks. Therefore, the endogenous response of technology restores the labor share and employment to initial levels arguing that in the long run the impact of automation on employment is small or null.

Similarly, Acemoglu and Restrepo (2017) study the impact of the increase in industrial robot usage between 1990 and 2007 on US local labor markets using a similar approach that the one developed by Autor et al. (2013). First, the authors show that in a model in which technology compete against labor in task production, robots and automation may reduce employment and wages. The authors confirm these results finding a negative relation between robot exposure and employment, and wages at the Commuting zone level. For instance, according to this study an additional robot per thousand worker reduces employment to population ratio by about 0.18-0.34 percentage point, and wages by 0.25-0.5 percentage points. Our project uses the database constructed by this study to assess the effect of automation on tasks off-shored in developing countries. We combine the data of industrial robots with WIOD and the census from IPUMS.

Finally, there are not papers that have explored the relationship between robots usage and employment or wages in developing countries. Nevertheless, there are several studies that have studied the skill biased technology change in the developing world and its implication on wage inequality and/or technology adoption. For instance, Berman and Machin (2000) analyze the skill-bias technolgy change in middle and low income countries using a sample of manufacturing industries. The authors find strong evidence of an increase in the relative demand for skill workers in middle-income countries such as Turkey, Peru, Colombia, or Portugal. On the other hand, they find less precise evidence in low-income countries. To measure the demand for skilled workers, they use the wage bill share for non-production workers.

Similarly, the increase in relative demand for skilled workers and technology adoption in developing countries is vastly associated with trade liberalization episodes in the 1980's and 1990's. In this context, several papers have found that trade and technology adoption induce an increase in relative wages between skilled and unskilled workers in developing countries increasing the skill premium and wage inequality (Hanson and Harrison, 1995; Feliciano, 2001; Verhoogen, 2008; Vogel and Burstein, 2012; Fieler et al., 2014). This was a striking result since one of the main prediction of the Stolper-Samuelson theorem was that trade liberalization would generate the opposite effect, a reduction in the skill premium.[5] However, there are several explanations for this result such as the quality upgrading mechanism proposed by Verhoogen (2008).

# 3 Data and Empirical Strategy

In this section, we describe the data and our empirical strategy. We use data from three different sources: 1) Robot adoption by industry provided by the *International Federation of Robotics* (IFR); 2) Trade flows across sectors and countries from BACI; and 3) Data on labor outcomes for each municipality in Mexico using IPUMS.

## 3.1 Some facts about robots

In this section we show some descriptive statistics of robots by sector and country. This data was purchased by the World Bank from the IFR and it is used by (Acemoglu and Restrepo, 2017) to assess the impact of robots in US local economies. According to their webpage, the IFR is an organization that connects the world of robotics around the world:

*"The International Federation of Robotics connects the world of robotics around the globe. Our members come from the robotics industry, national or international industry associations and Research and Development institutes. Our federation represents over 50 members from more than 20 countries. The IFR statistical department is the primary global resource for data on robotics. The IFR was established as a non-profit organization in 1987."*

The IFR data covers approx 70 countries from 1993 to 2015, corresponding to about 90 percent of the industrial robots market. Nevertheless, one important caveat is that the break down by industry is only for few countries and there are differences across countries in the initial year. For instance, most European countries have data by sector since 1993, while for the US it only starts since 2004 and for Mexico in 2011. Thus, for our empirical strategy when we construct the change in robots we use 2004 as our baseline year for the US, and 2011 for Mexico.

Using the data of robots aggregated by country and sector, we explore some basic questions

[5]This result is analyzed more deeply by Goldberg and Pavcnik (2007) that discuss the empirical evidence of the distribtutional effects of globalization in developing countries.

such as which country or sector has adopted more robots in recent years? Figures 2 and 3 show these statistics. For the case of sectors, most of the robots have been adopted in the automotive sector, while in the case of countries, South Korea, Japan, Germany and Singapore are the places that have adopted more of these industrial robots.

Figure 2: Robots by Industry

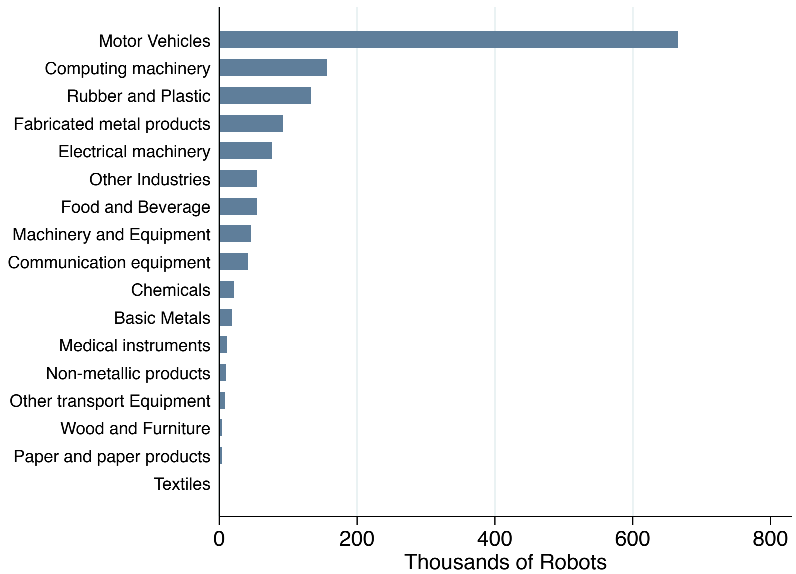
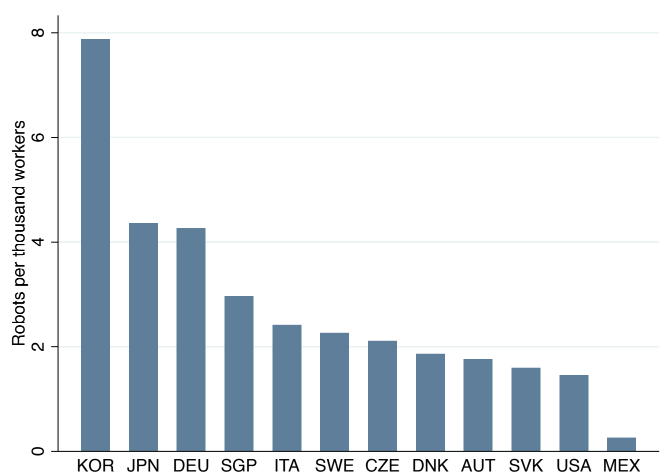



Figure 3: Robots by Country




From figure 3, the reader can also infer that developing countries have adopted some robots, but this number is low relative to advanced economies. For instance, robot adoption in Mexico is less than 15 times robot adoption in Korea, Japan, or Germany. Therefore, while there can be some negative direct impact of robot adoption in developing in the future, it seems that so far the negative consequences would come from trade channels and offshoring, which corresponds precisely to the mechanism explored in this study. In the next section we document three empirical facts found in the data.

### 3.2 Empirical facts

We start studying the relationship between robot adoption and trade patterns. To that end, we match the information from the IFR to trade flows from BACI. We use trade flows at the 6 digit HS-92 level and aggregate the data to countries and 2 digit ISIC sectors using the correspondence tables from the World Bank.

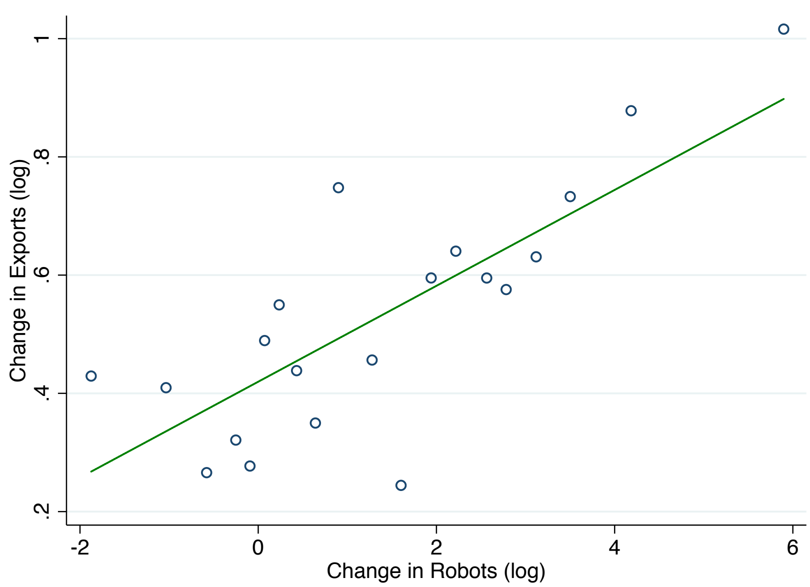
***Empirical Fact 1: There is a positive correlation between trade flows and robots.***

In our first specification, we relate changes in exports to changes in robots adopted by exporters in the following way:

$$\Delta \log X_{ijs}^{2004-2014} = \gamma_0 + \gamma_1 \Delta \log \text{Rob}_{is}^{2004-2014} + \psi_{ij} + \psi_s + \epsilon_{ijs} \tag{1}$$

Where $X_{ijs}$ are exports in sector $s$ to country $j$ stemming from country $i$, and $\text{Rob}_{is}$ are industrial robots adopted by country $i$ in sector $s$. Equation 1 is a gravity equation in which we add robots as an explanatory variable. Our main hypothesis is that trade flows are positively related to robots adoption, which implies that $\gamma_1 > 0$. We confirm our hypothesis in figure 4 and table 1.

Figure 4: Bin-scatter Trade flows and Robots



From this figure, we conclude that there is a positive relationship between the change in robots from 2004 to 2014 and the change in exports. In particular country-sectors that adopt more robots export more to other countries. We confirm our hypothesis estimating equation 1 adding a bunch of fixed effects, including country and sector fixed. The results are presented in the table below.

Table 1: Trade Flows and Robots

| | Δ Tradeflows (dif in logs) | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Δ Robots Exporter (dif in logs) | 0.076*** | 0.082*** | 0.077*** | 0.014* | 0.013* |
| | (0.006) | (0.004) | (0.006) | (0.008) | (0.007) |
| Sector FE | Yes | No | Yes | Yes | Yes |
| Importer FE | No | Yes | Yes | Yes | - |
| Exporter FE | No | No | No | Yes | - |
| Exporter-Importer FE | - | - | - | - | Yes |
| Observations | 17079 | 17079 | 17079 | 17079 | 17079 |
| R-squared | 0.068 | 0.151 | 0.206 | 0.263 | 0.327 |

This table relates the change in tradeflows to the change in robots. Trade flows are constructed using the information provided by BACI, and the information on robots is provided by the IFR. Robust standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

From the results, we conclude that an increase in the change of robots of 1% by the exporter country is associated with an increase on trade flows between 0.013% and 0.076% to other countries. Overall, these results confirm that our main mechanism of study: the trade channel is important, since advanced economies are increasing their terms of trade relative to developing countries in different sectors. Therefore, we proceed to analyze which sectors in terms of comparative advantage are the ones in which advanced economies are adopting robots.

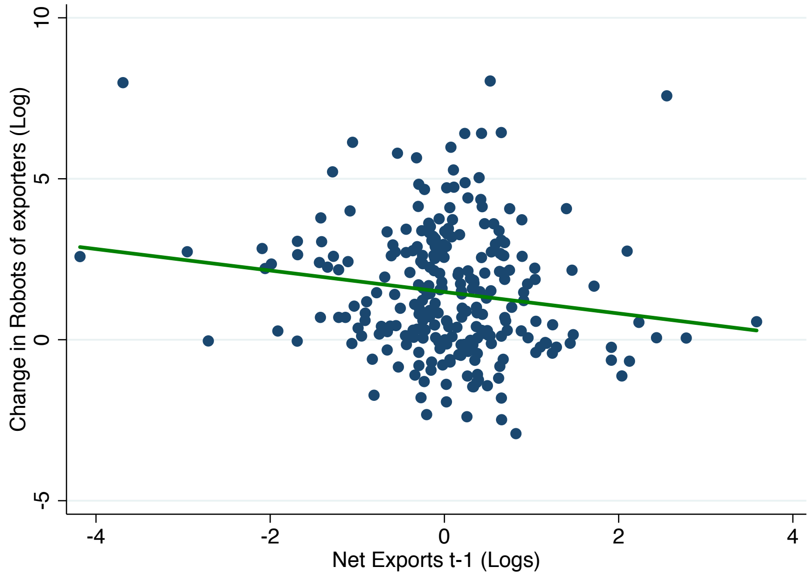
***Empirical Fact 2: There is a negative correlation between robots and trade deficits, implying that advanced economies are adopting robots in sectors in which traditionally they have comparative disadvantage.***

To test in which sectors are advanced economies adopting robots, we relate changes in robot adoption between 2004 and 2014 with net exports in 2004 estimating the following equation:

$$\Delta \log Rob_{is}^{2004-2014} = \beta_0 + \beta_1 \Delta \text{Net log flows}_{is}^{2004} + \epsilon_{is} \tag{2}$$

Where Net log flows$_{is}^{2004}$ is the log of exports minus imports in country $i$, sector $s$ in 2004. If advanced countries are adopting more robots in the sectors with less comparative advantage, then, $\beta_1 < 0$. Figure 5 shows this relationship.

Figure 5: Robots and Sectoral Trade Deficits




This figure shows the negative relationship between robots adopted in sector *s*-country *i* and net exports in 2004.

From the figure above, we infer that there is a negative relationship between robots adopted and trade deficits, implying that high income countries are adopting robots in sectors with less comparative advantage.[6] In the next section, we describe our empirical strategy in which we relate robots and net exports to labor outcomes in Mexico for a case study.

### 3.3 Empirical Strategy

In this section we describe our methodology to relate Mexican labor outcomes to net exports to the US, and robots adopted in the US. Our work follows the empirical strategy implemented in Autor et al. (2013) and Acemoglu and Restrepo (2017). In particular, we construct a measure of exposure to trade and robots at the local level using Bartik shocks. In our framework, a region is more exposed to these shocks if it employs more labor (or income) in sectors that are adopting robots in the U.S.

In our main specification we relate Net Exports to robot adoption and labor outcomes to Net Exports to test the trade mechanism of our interest.[7] For this part we construct labor outcomes using the data provided by IPUMS. In particular, we use the Mexican census of 2000 and 2015. Our main specification is:

[6] The point estimate of this regression is -0.33 and significant at 5%. When we include country and sector fixed effects, the estimate is not longer significant.

[7] We estimate a robustness check using change in robots from other countries instead of the US. The idea is that robots in the US may directly impact labor outcomes in Mexico, therefore, we use another instrument to test our results.

$$\Delta y_m = \alpha_0 + \alpha_1 \text{Net Exp.}_m + \gamma_{d(m)} + \epsilon_m \tag{3}$$

Where $\Delta y_m$ is some labor outcome at municipality $m$ and $\gamma_{d(m)}$ is a state fixed effect. In our framework we consider two labor outcomes: the employment to population ratio and log earnings. On the other hand, Net Exp.$_m$ corresponds the exposure to net exports defined as a Bartik Shock at the municipality level:

$$\text{Net Exp.}_m \equiv \sum_{s=1}^{S} \ell_{ms,2000} \cdot \frac{\Delta \text{Net Exports}_{s,2004-2014}^{MEX,USA}}{L_{s,2000}^{MEX}}$$

Where $\ell_{ms,2000}$ is the labor share of industry $s$ at municipality $m$ in 2000.[8] Since we are interested to test the impact of robots through trade, in a first stage, we relate the exposure to net exports to robot adoption in the US. Our specification is shown in the following equation:

$$\text{Net Exp.}_m = \delta_0 + \delta_1 \text{Robots Exp.}_m + \gamma_{p(m)} + \nu_m \tag{4}$$

$$\text{Robots Exp.}_m \equiv \sum_{s=1}^{S} \ell_{ms,2000} \cdot \frac{\Delta \text{Robots}_{s,2004-2014}^{USA}}{L_{s,2004}^{USA}/1000}$$

Where Robots Exp.$_m$ is a measure of exposure to robots at the municipality level. Our main hypothesis is that $\delta_1 < 0$, since this implies that higher robots in the US are associated with lower net exports stemming from Mexico to the US. All our regressions are weighted by the working age population, and we include as a covariate the exposure to Mexican Robots, finally, we compute standard errors with clusters at the state level. In the next section we present some descriptive statistics of our data at the municipality level.

### 3.4 Descriptive Stats

Table 2 shows summary statistics of our main variables. On average, in 2000, the employment to population ratio is 38.95% in Mexican municipalities, this average is very similar for low skilled workers, nevertheless, for high skilled workers this ratio is larger, since on average 81.93% of this type of workers were employed at the base line year. On the other hand, when we consider changes between 2000 and 2015, this ratio has decreased in 1.99 p.p. for all workers, 2.46 p.p for low skilled workers and 11.60 p.p. for high skilled workers. Finally, in terms of income, average income has increased in 3.75% for all workers.

[8] We construct the share using labor earnings instead of workers. We believe this is a better definition to capture labor effective units.

Table 2: Summary statistics

| Panel A: Outcomes | | | | | |
|---|---|---|---|---|---|
| Variable | Mean | SD | 10th Perc. | 50th Perc. | 90th Perc. |
| Employment to population ratio | 38.95 | 10.40 | 24.94 | 39.90 | 51.47 |
| Employment to population ratio LS | 38.02 | 10.27 | 24.30 | 39.04 | 50.36 |
| Employment to population ratio HS | 81.93 | 15.05 | 66.67 | 83.14 | 100.00 |
| Δ in employment to population ratio | -1.99 | 8.40 | -11.24 | -1.14 | 6.82 |
| Δ in eployment to population ratio LS | -2.46 | 8.36 | -11.49 | -1.84 | 6.41 |
| Δ in eployment to population ratio HS | -11.60 | 18.20 | -29.60 | -11.11 | 4.74 |
| Δ in log Earned Income | 3.75 | 1.12 | 2.89 | 3.60 | 4.56 |
| Δ in log Earned Income LS | 1.65 | 0.16 | 1.44 | 1.65 | 1.86 |
| Δ in log Earned Income HS | 0.94 | 0.37 | 0.55 | 0.96 | 1.33 |
| Panel B: Exposure | | | | | |
| Variable | Mean | SD | 10th Perc. | 50th Perc. | 90th Perc. |
| Exposure to Net Exports | -0.63 | 1.23 | -1.95 | -0.67 | 0.50 |
| Exposure to Robots in Mexico | 0.11 | 0.25 | 0.01 | 0.02 | 0.27 |
| Exposure to Robots in the US | 3.46 | 3.64 | 0.64 | 2.81 | 6.28 |
| Observations | | | 2210 | | |

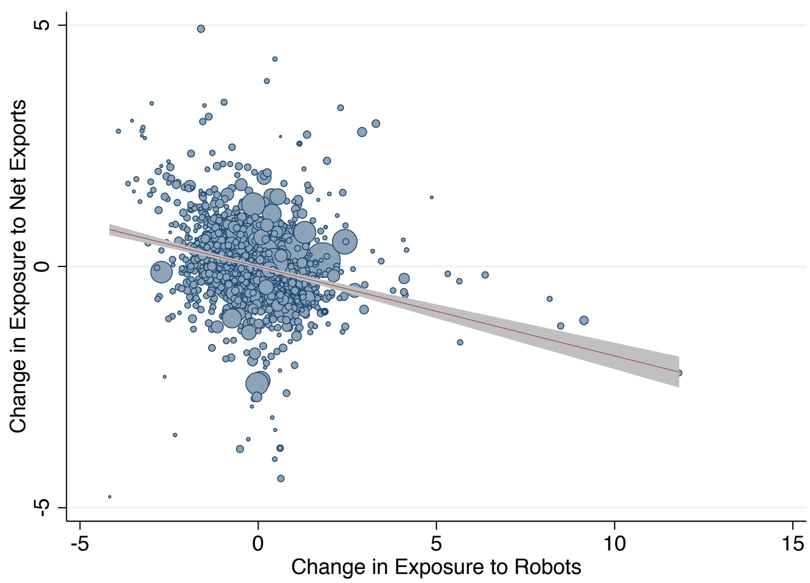
This table presents summary statistics of our main variables of the data at the municipality level for both the initial values and changes.

When we analyze the variables of exposure we can see two patterns. On one hand, there is enough variation in the exposure to net exports suggesting that the industry composition differs across municipalities, which is the main variation that we want to exploit. On the other hand, the exposure to robots to the US varies more than the exposure to robots in Mexico, this result comes from the fact that robots adopted in Mexico are less volatile across sectors than the ones in the US. In the next section we discuss our main findings.

## 4 Results on Labor Outcomes

In this section we discuss our main results relating labor outcomes to net exports and robots. We start estimating equation 4 by OLS, figure 6 shows a scatter plot of the first stage after residualizing both variables with the exposure to Mexican robots and state fixed effects. Each dot corresponds to a municipality and it is weighted by the population size.

Figure 6: First Stage




From the figure above, we infer that as expected, there is a negative relation between robots exposure and net exports exposure, which implies that if there are more robots adopted in the US, exports stemming from Mexico are lower relative to imports from the US to Mexico. In particular, the coefficient of this regression is -0.19, which implies that one more robot per thousand workers is associates with a decrease of 0.19 thousand dollars of net exports. Finally, the F statistic of this regression is 28.87 which implies that we have a strong first stage.

We proceed to estimate equation 3 by two stage least square. Our results for both the first and second stage are presented below in table 3. Overall, there is a negative association between robots adopted in the US and local labor outcomes via a trade channel.

In particular, one robot adopted per thousand workers in the US decreases net exports exposure in 0.19 thousand dollars at the municipality level, while a decadal increase of a thousand dollars in terms of net exports increases the employment to population ratio in 1.5 p.p. This result implies that the reduced form, in which we correlate labor outcomes with robot exposure in the US has a negative coefficient. For instance, the reduced form estimates imply that one more robot per thousand workers in the US decreases the employment to population ratio in 0.25 p.p. and log income in 0.04% in Mexico.

Table 3: Results: Local Labor Markets

| Net Exports and Robot Exposure | (1) | (2) | (3) |
|---|---|---|---|
| | FS | OLS | IV |
| Panel A: Employment Share | | | |
| Robots Exp. USA | -0.194*** | | |
| | (0.036) | | |
| Net Exports Exp. | | 1.569** | 1.323** |
| | | (0.714) | (0.717) |
| Robot Exp. Mexico | 6.12*** | 0.157 | -2.272 |
| | (0.515) | (0.177) | (2.514) |
| Panel B: Log Earned Income | | | |
| | FS | OLS | IV |
| Robots Exp. USA | -0.194*** | | |
| | (0.036) | | |
| Net Exports Exp. | | -0.065*** | 0.213** |
| | | (0.019) | (0.089) |
| Robot Exp. Mexico | 6.12*** | -0.301*** | -1.218 |
| | (0.515) | (0.111) | (0.315) |
| F statistic-FS | 28.87 | | |
| N | 2210 | 2210 | 2210 |
| State Fixed Effects | Yes | Yes | Yes |

This table shows the results for the first stage and second stage of our main specification. In a first stage, we instrument Net Exports exposure to robot exposure in the US, and in a second stage we relate local labor outcomes to Net exports. We compute standard errors by clusters at the state level. *** p<0.01, ** p<0.05, * p<0.1.

What are the implications of our results in terms of size on labor outcomes, the difference between the 25th and 75th percentiles on robot exposure across Mexican municipalities is 2.6. Therefore, if we move a municipality from the 25th percentile to the 75th percentile in terms of robot exposure, the employment share would have decreased in 0.67 pp, and average earnings in 0.11%. These findings seem small but plausible.[9]

We proceed to disentangle the effect of robot adoption in the US between low skilled and high skilled workers in Mexico. We estimate equation 3 for both groups of workers. This exercise is important because one of our predictions is that robots by advanced countries are adopted in sectors in which they have less comparative advantage. Therefore, through the lens of the Stolper-Samuelson theorem we should expect that robots in the US have a bigger impact on low-skilled than in high skilled worker.[10]

[9]We also run a specification in which we instrument robots exposure in the US with robot exposure from other countries using labor shares in 1990, which is a similar empirical specification than the one by Acemoglu and Restrepo (2017). We find that...

[10]A similar effect is captured in our model in section 5.

Table 4 shows our main results for low and high skilled workers. From the table, we observe that for low skilled workers the expected results hold. For instance, there is a negative relationship between Net exports and robots in the US, and a positive relationship between low skilled labor outcomes and net exports. The reduced form estimates from this regression imply that a robot per thousand workers adopted in the US is associated with a decrease in the employment to population ratio of 0.27 p.p. and on average earnings in 0.009%. In terms of the magnitude, if we move a municipality from the 25th to the 75th percentile, the employment to population ratio decreases in 0.72 p.p. and average earnings decrease in 0.024%.

Table 4: Results: High and Low skilled workers

| Net Exports and Robot Exposure | Low skilled workers | | High skilled workers | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Panel A: Employment Share | | | | |
| | OLS | IV | OLS | IV |
| Net Exports Exp. | 0.123 | 1.389* | 0.167 | -3.570** |
| | (0.177) | (0.708) | (0.367) | (1.473) |
| Robot Exp. Mexico | 1.009 | -3.170 | 6.181*** | 18.56*** |
| | (0.719) | (2.469) | (1.779) | (5.058) |
| Panel B: Log Earned Income | | | | |
| | OLS | IV | OLS | IV |
| Net Exports Exp. | -0.091*** | 0.049* | -0.003 | -0.016 |
| | (0.027) | (0.027) | (0.008) | (0.033) |
| Robot Exp. Mexico | -0.026*** | -0.343*** | 0.014 | 0.055 |
| | (0.005) | (0.098) | (0.038) | (0.114) |
| N | 2210 | 2210 | 2080 | 2080 |
| State Fixed Effects | Yes | Yes | Yes | Yes |

This table shows the results for the first stage and second stage of our main specification for low and high skilled workers. In a first stage, we instrument Net Exports exposure to robot exposure in the US, and in a second stage we relate local labor outcomes to Net exports. We compute standard errors by clusters at the state level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

On the other hand for high skilled workers, in terms of the reduced form the effect is only significant for employment, but not for income. In particular if we move a municipality from the 25th to the 75th percentile, the employment to population ratio increase in 1.76 p.p. In the appendix we proceed to develop a model to rationalize some of these facts. The model is based on Armington (1969) and Acemoglu and Restrepo (2017).

## 5 Final Remarks

In this preliminary study, we showed that robots in advanced economies may have important implications on labor outcomes in developing countries through trade. Using data on robots adoption and trade trends in different countries, we derived three facts: 1) countries that adopt automation technologies export more to the world; 2) advanced economies are adopting robots in sectors in which they have a traditional comparative disadvantage; and 3) using Mexico as a case study, we find that robot adoption in the US has had some negative consequences on labor market outcomes in the Mexican economy, especially on low-skilled workers.[11]

In the appendix, we develop an Armington model of tasks, based on the work by (Acemoglu and Restrepo, 2017). Our model replicates different facts found in the data. For example, robot adoption increases trade flows, and advanced economies are more propense to adopt robots. In the next steps, we want to add to our theoretical results, more sectors and different type of workers to rationalize our findings on the skill premium and the adverse effects on low skilled workers.

Moreover, in the future, we want to take the data to the model more seriously. For example, estimate our model more structurally. One possibility is to assume that $\gamma(\omega)$ is an increasing function on the index of tasks which imply that the higher the task index, the higher the relative efficiency of labor relative to robots. Then using data on occupations we would be able to estimate $\gamma$ as a function of $\omega$.

Finally, this document is still very preliminary, and we are working to improve both the empirical part and the theoretical model in the appendix.

[11] In the empirical part in which we regress Mexican labor outcomes and robots in the US, we are not finding robust results. We are estimating two different models: 1) we are instrumenting robot adoption in the US with robot adoption in other high income countries (same strategy as (Acemoglu and Restrepo, 2017) due to endogeneity concerns; and 2) we are using data on occupations to test the impact of robots in other countries on other labor outcomes.

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# A Model

The model has two components: first, it consists of a representative firm by country and sector, that produces with high and low skilled workers. Each worker produces a continuum of tasks that can be replaced by robots. As in Acemoglu and Restrepo (2017), the decision of replacing human labor by robots depends on the productivity of workers relative to robots, relative factor prices and the technology available. We then use this structure and add it to a multisector Armington model. The following section describes the firms' problem and production technology:

### Production function

The production function of country $j$ and sector $s$ depends on high skilled inputs ($H_{js}$), low skilled inputs ($L_{js}$) and a country-sector specific productivity term $A_{js}$:

$$Y_{js} = A_{js}\left(\theta_{js}^{\frac{1}{\rho_s}} L_{js}^{\frac{\rho_s - 1}{\rho_s}} + (1-\theta_{js})^{\frac{1}{\rho_s}} H_{js}^{\frac{\rho_s - 1}{\rho_s}}\right)^{\frac{\rho_s}{\rho_s - 1}}$$

Each input produces tasks. Workers and machines are the two factors that can produce those tasks and are perfect substitutes in the production of each task.[12] For both, low skilled and high skilled tasks there is a technology frontier denoted by $M_{sl}$ and $M_{sh}$. However, each country and sector decides based on this technology frontier, relative productivity between workers and robots, and relative factor prices the measure of tasks that are automated. Let denote $M_{js,l}$ and $M_{js,h}$ the measure of low-skilled and high-skilled tasks that are automated in sector $s$, country $j$, then:

$$L_{js} = \left(\int_0^1 L_{js}^{\frac{\varepsilon-1}{\varepsilon}}(\omega) d\omega\right)^{\frac{\varepsilon}{\varepsilon-1}}$$

with

$$L_{js}(\omega) = r_{js,l}(\omega) + \gamma_{js,l} l_{js}(\omega) \; if \; \omega \leq M_{s,l}$$

in the case of the specific country

$$L_{js}(\omega) = r_{js,l}(\omega)) \; if \; \omega \leq M_{js,l}$$

and

$$L_{js}(\omega) = \gamma_{js,l} l_{js}(\omega) \; if \; \omega > M_{js,l}$$

In the case of high skill

$$H_{js} = \left(\int_0^1 H_{js}^{\frac{\varepsilon-1}{\varepsilon}}(\omega) d\omega\right)^{\frac{\varepsilon}{\varepsilon-1}}$$

with

$$H_{js}(\omega) = r_{js,h}(\omega) + \gamma_{js,h} h_{js}(\omega) \; if \; \omega \leq M_{s,h}$$

[12] In other words, in the production of each tasks the firm uses only robots or workers.

in the case of the specific country

$$H_{js}(\omega) = r_{js,h}(\omega))\ if\ \omega \leq M_{js,h}$$

and

$$H_{js}(\omega) = \gamma_{js,h} h_{js}(\omega)\ if\ \omega > M_{js,h}$$

As mentioned above, $M_{js,h}$ and $M_{js,l}$ represent the tasks that are automated in each country, sector and skill level. We assume that all the task $\omega$ that are lower than $M_{js,i}$ are automated and that $M_{js,i} = F(M_s, w_{j,i}, \gamma_{js})$, where $M_s$ is a global technological level that shows how automated are some sectors, $\gamma_{js}$ shows some country-specific conditions and $w_{j,i}$ are the specific wages in the country and for high and low skilled. Then, $M_{js,h}$ and $M_{js,l}$ will be defined endogenously in the model, as the wages are defined endogenously, but conditional on that value, the firm will decide by this rule how much to produce with robots and labor, then we obtain that

$$L_{js} = \left( \int_0^{Mjs,l} r_{js,l}^{\frac{\varepsilon-1}{\varepsilon}}(\omega) d\omega + \int_{Mjs,l}^{1} \left(\gamma_{js,l} l_{js,l}\right)^{\frac{\varepsilon-1}{\varepsilon}}(\omega) d\omega \right)^{\frac{\varepsilon}{\varepsilon-1}}$$

and

$$H_{js} = \left( \int_0^{Mjs,h} r_{js,h}^{\frac{\varepsilon-1}{\varepsilon}}(\omega) d\omega + \int_{Mjs,h}^{1} \left(\gamma_{js,h} h_{js,h}\right)^{\frac{\varepsilon-1}{\varepsilon}}(\omega) d\omega \right)^{\frac{\varepsilon}{\varepsilon-1}}$$

or

$$L_{js} = \left( M_{js,l} r_{js,l}^{\frac{\varepsilon-1}{\varepsilon}} + (1 - M_{js,l}) \left(\gamma_{js,l} l_{js}\right)^{\frac{\varepsilon-1}{\varepsilon}} \right)^{\frac{\varepsilon}{\varepsilon-1}}$$

and

$$H_{js} = \left( M_{js,h} r_{js,h}^{\frac{\varepsilon-1}{\varepsilon}} + (1 - M_{js,h}) \left(\gamma_{js,h} h_{js}\right)^{\frac{\varepsilon-1}{\varepsilon}} \right)^{\frac{\varepsilon}{\varepsilon-1}}$$

Then, we have that $M_{js,l}$ and $M_{js,h}$ depend on the price of robots $q_{s,i}$, the wages $w_{j,i}$ and the productivity $\gamma_{js,i}$ for $i = l, h$. Then, we have that

$$\omega < M_{js,l}\ if\ \frac{w_{j,l}}{q_{s,l}} < \gamma_{js,l}\ \&\ \omega < M_{s,l}$$

and

$$\omega < M_{js,h}\ if\ \frac{w_{j,h}}{q_{s,h}} < \gamma_{js,h}\ \&\ \omega < M_{s,h}$$

Then, in order to get $M_{js,h}$ and $M_{js,l}$ we need to determine wages and robots's prices. From the FOC of the firm we have that

$$\frac{w_{j,h} h_{js}^{\frac{1}{\varepsilon}}}{(1 - M_{js,h}) \gamma_{js,l}^{\frac{\varepsilon-1}{\varepsilon}}} = \frac{q_{s,h} r_{js,h}^{\frac{1}{\varepsilon}}}{M_{js,h}}$$

and

$$\frac{w_{j,l} l_{js}^{\frac{1}{\varepsilon}}}{(1 - M_{js,l}) \gamma_{js,l}^{\frac{\varepsilon-1}{\varepsilon}}} = \frac{q_{s,l} r_{js,l}^{\frac{1}{\varepsilon}}}{M_{js,l}}$$

Then $M_{js,l}$ and $M_{js,h}$ will be determined by:

$$M_{js,l} = \frac{\frac{q_{s,l}}{w_{j,l}} r_{js,l}^{\frac{1}{\varepsilon}} \gamma_{js,l}^{\frac{\varepsilon-1}{\varepsilon}}}{l_{js}^{\frac{1}{\varepsilon}} + \frac{q_{s,l}}{w_{j,l}} r_{js,l}^{\frac{1}{\varepsilon}} \gamma_{js,l}^{\frac{\varepsilon-1}{\varepsilon}}}$$

and

$$M_{js,h} = \frac{\frac{q_{s,h}}{w_{j,h}} r_{js,h}^{\frac{1}{\varepsilon}} \gamma_{js,h}^{\frac{\varepsilon-1}{\varepsilon}}}{h_{js}^{\frac{1}{\varepsilon}} + \frac{q_{s,h}}{w_{j,h}} r_{js,h}^{\frac{1}{\varepsilon}} \gamma_{js,h}^{\frac{\varepsilon-1}{\varepsilon}}}$$

Plus the other conditions

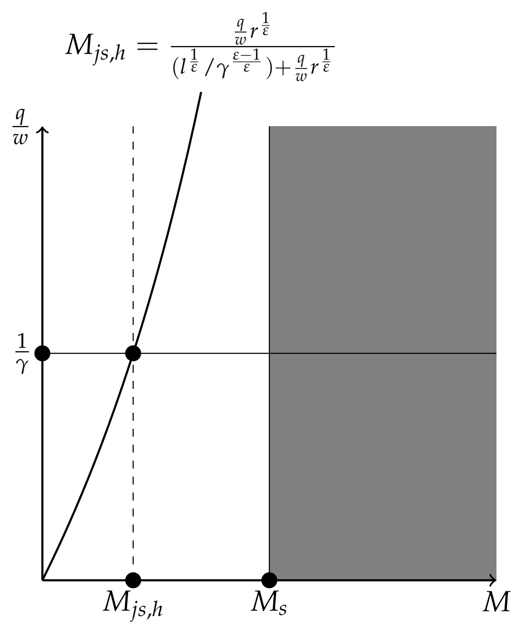
$$\frac{w_{j,l}}{q_{s,l}} < \gamma_{js,l}$$
$$\frac{w_{j,h}}{q_{s,h}} < \gamma_{js,h}$$

and

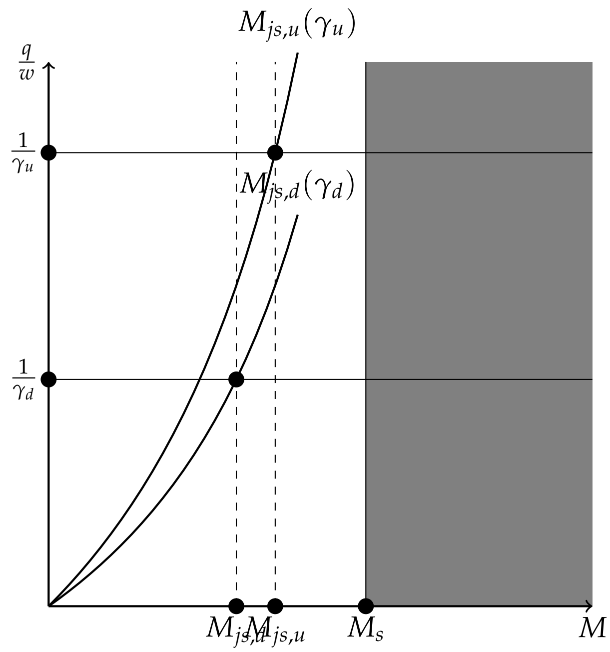
$$M_{js,l} \leq M_{s,l}$$

$$M_{js,h} \leq M_{s,h}$$

so, we have




Thus, according to this model, and considering this partial equilibrium analysis, new technologies that increase $M_s$ only will benefit economies with low productivity if we consider $\gamma_d$ as the productivity of a developed country and $\gamma_u$ as the productivity of a developing country. Then, with an increase in productivity we get the following result:




As we can see in the notation, the price of the robots is determined in the international market. We assume that both countries are small to affect the price, then we have that the price of robots is constant and taken as given. Therefore, the number of robots adopted is going to be determined by the following condition:

$$w_{js,l} = q_{s,l}\gamma_{js,l}$$

and

$$w_{js,h} = q_{s,h}\gamma_{js,h}$$

Also, from the FOC over labor we have:

$$w_{js,l} = A_{js}\left(\theta_{js}^{\frac{1}{\rho_s}} L_{js}^{\frac{\rho_s-1}{\rho_s}} + (1-\theta_{js})^{\frac{1}{\rho_s}} H_{js}^{\frac{\rho_s-1}{\rho_s}}\right)^{\frac{1}{\rho_s-1}} \theta_{js}^{\frac{1}{\rho_s}} L_{js}^{\frac{-1}{\rho_s}} (1-M_{js,l})\gamma_{js,l}^{\frac{\varepsilon-1}{\varepsilon}} l_{js}^{\frac{-1}{\varepsilon}}$$

and

$$w_{js,h} = A_{js}\left(\theta_{js}^{\frac{1}{\rho_s}} L_{js}^{\frac{\rho_s-1}{\rho_s}} + (1-\theta_{js})^{\frac{1}{\rho_s}} H_{js}^{\frac{\rho_s-1}{\rho_s}}\right)^{\frac{1}{\rho_s-1}} (1-\theta_{js})^{\frac{1}{\rho_s}} H_{js}^{\frac{-1}{\rho_s}} (1-M_{js,h})\gamma_{js,h}^{\frac{\varepsilon-1}{\varepsilon}} h_{js}^{\frac{-1}{\varepsilon}}$$

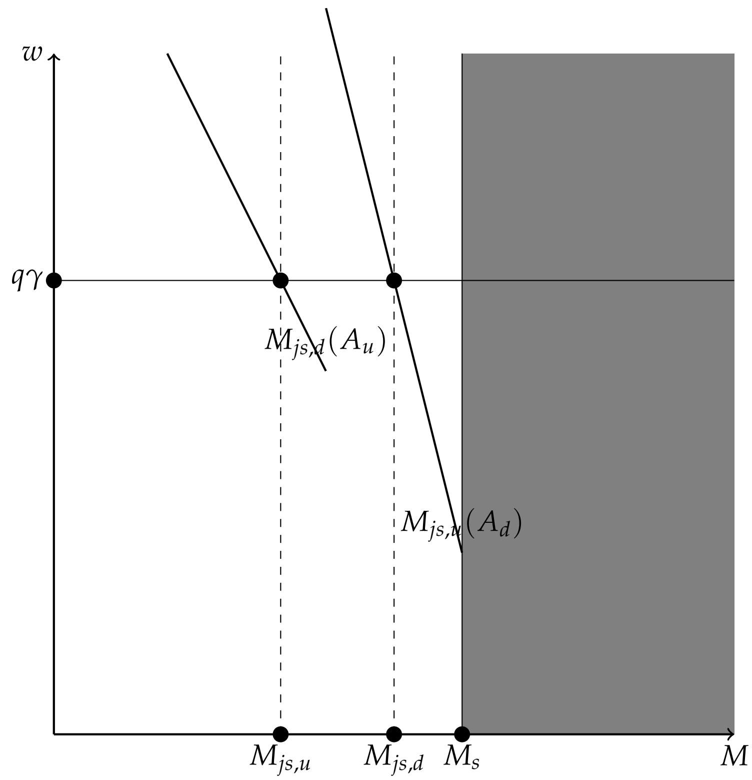
or

$$w_{js,l} = A_{js}\gamma_{js,l}^{\frac{\varepsilon-1}{\varepsilon}} l_{js}^{\frac{1}{\varepsilon}} Y_{js,l}^{'}(1-M_{js,l})$$

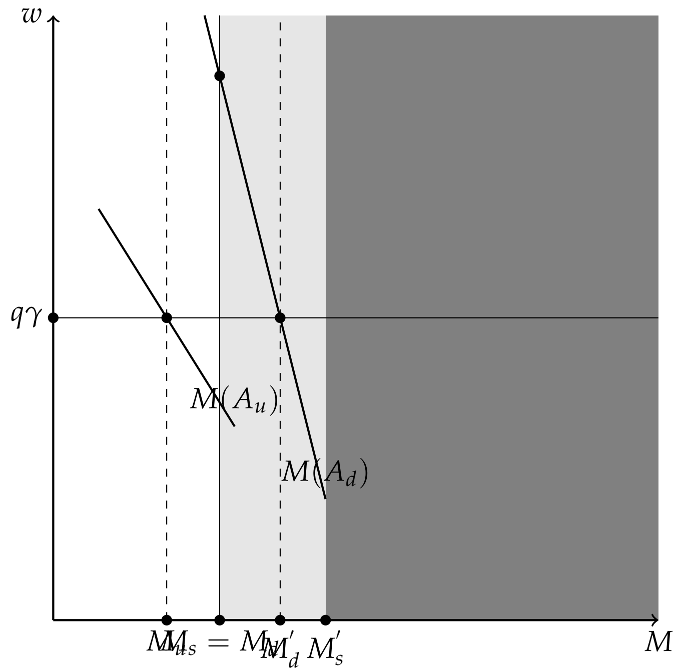
and

$$w_{js,h} = A_{js}\gamma_{js,h}^{\frac{\varepsilon-1}{\varepsilon}} h_{js}^{\frac{1}{\varepsilon}} Y'_{js,h}(1 - M_{js,h})$$

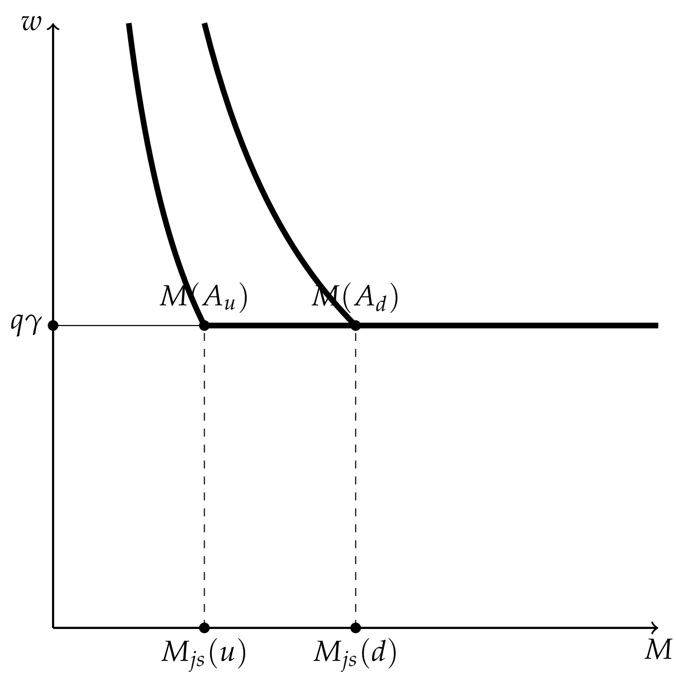
The question now is how advanced countries will adopt robots relative to less developed countries. We define $A_d$ as the productivity of developed countries and $A_u$ the productivity of developing countries, with $A_d > A_u$, then:




Now, what happens if there is a technological improvement that increases the tasks that are potentially replaced by robots $M_s$ and one country is at the robots frontier, then that country will increase the number of robots. However, the country away from the frontier will use the same amount of robots before the shock, so we see in this partial equilibrium version of the model, that more developed countries will use more robots and also adopt new robots, while countries away from the frontier will not adopt these robots.




Then, wages in both countries depend on how restrictive is for each country the frontier technology and on the price of robots. For a less advanced country, the price of robots determines the wages, while for advanced economies, the wage is higher until certain level of development in automation is reached, or in other words, as $M_s$ increases, there is convergence in the wages between the advanced and the less advanced country.



Hitherto, we have studied our results in partial equilibrium. In the next section, we add our production function technology to an Armington framework to close the model in GE. This analysis will help us to understand the implications of automation on trade patterns. For instance, as advanced economies adopt new robots, their cost of production in those sectors will be cheaper. As those countries have a higher productivity, the rest of the world might substitute consumption from poor to rich countries in some sectors. This could have implications in labor markets in the develop and the developing countries. We explore this analysis in the next section.

### A.1 Trade Model

We use the production structure described above and add it to a model where different countries trade. In particular, each country produces a variety of a good that enters into a constant elasticity of substitution (CES) utility function of consumers. Each country produces goods in all sectors indexed by $s$. The utility function is a Cobb-Douglas aggregation of all these sectors. There are no parameters that impose home bias in consumption, but the good is subject to a trade cost $\tau_{j,n,s} \geq 0$ from country $j$ to country $n$, that is symmetrical and equal to one for the local good consumed in each country. Formally, the utility function takes the following form:

$$U_n = \prod_{s=1}^{S} X_{ns}^{\beta_{ns}}$$

$$X_{ns} = \left[ \sum_{j=1}^{N} X_{jn,s}^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}$$

We use the production structure from the previous section. The parameters $M_{js,h}$ and $M_{js,l}$ represent the tasks that are automated in each country, sector and skill level. We assume that all the task $\omega$ that are lower than $M_{js,i}$ are automated and that $M_{js,i} = F(M_s, w_{j,i}, \gamma_{js})$, where $M_s$ is a global technological level that shows how automatable are some sectors, $\gamma_{js}$ captures the relative efficiency of human labor vs robots, and $w_{j,i}$ are the specific wages in country $j$ for high and low skilled. Then, $M_{js,h}$ and $M_{js,l}$ will be defined endogenously in the model, as the wages are determined endogenously depending on the supply, given by the firms' problem and the demand, given by the trade structure.

In equilibrium, we solve the following system of equations:

$$M_{js,l} = \min \left[ M_{s,l}, \left( \frac{\frac{q_l}{w_{j,l}} r_{js,l}^{-1/\varepsilon}}{\left(\gamma_{js,l} l_{js}\right)^{-1/\varepsilon} + \frac{q_l}{w_{j,l}} r_{js,l}^{-1/\varepsilon}} \right) \right]$$

$$M_{js,h} = \min \left[ M_{s,l}, \left( \frac{\frac{q_h}{w_{j,h}} r_{js,h}^{-1/\varepsilon}}{\left(\gamma_{js,h} h_{js}\right)^{-1/\varepsilon} + \frac{q_h}{w_{j,h}} r_{js,h}^{-1/\varepsilon}} \right) \right]$$

$$I_{js} = \sum_n \frac{p_{jj,s}^{1-\sigma}\tau_{jn,s}^{1-\sigma}}{P_{n,s}^{1-\sigma}}\beta_{ns}\left(w_{n,l}\bar{L}_n + w_{n,h}\bar{H}_n + \frac{q_l R_l}{N} + \frac{q_h R_h}{N}\right) \quad \forall js \tag{5}$$

$$\frac{\kappa_{jl,s} L_{js}^{\frac{1}{\rho_s}}}{\theta_{j,s}^{\frac{1}{\rho_s}}} = \frac{\kappa_{jh,s} H_{js}^{\frac{1}{\rho_s}}}{(1-\theta_{j,s})^{\frac{1}{\rho_s}}} \quad \forall js \tag{6}$$

$$\frac{\kappa_{jl,s} L_{js}^{\frac{1}{\rho_s}}}{\theta_{j,s}^{\frac{1}{\rho_s}}} = \frac{\kappa_{jh,s} H_{js}^{\frac{1}{\rho_s}}}{(1-\theta_{j,s})^{\frac{1}{\rho_s}}} \quad \forall js \tag{7}$$

$$\sum_s l_{js} = \bar{L}_j \quad \forall j \tag{8}$$

$$\sum_s h_{js} = \bar{H}_j \quad \forall j \tag{9}$$

$$\sum_j \sum_s r_{js,l} = \bar{R}_l \tag{10}$$

$$\sum_j \sum_s r_{js,h} = \bar{R}_h \tag{11}$$

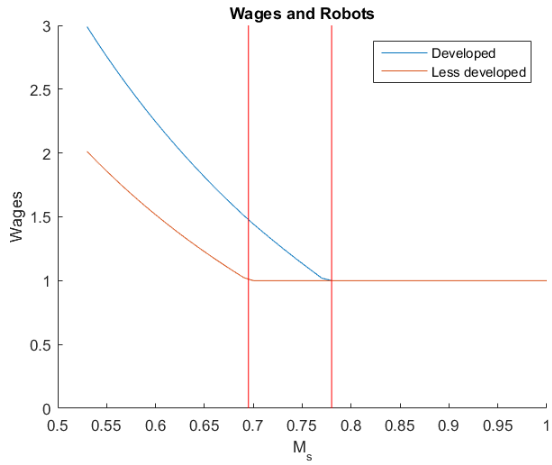
$$\kappa_{jl,s} = \left[M_{js,l}^{\epsilon} q_l^{1-\epsilon} + (1-M_{js,l})^{\epsilon}\left(\frac{w_{j,l}}{\gamma_{js,l}}\right)^{1-\epsilon}\right]^{\frac{1}{1-\epsilon}}$$

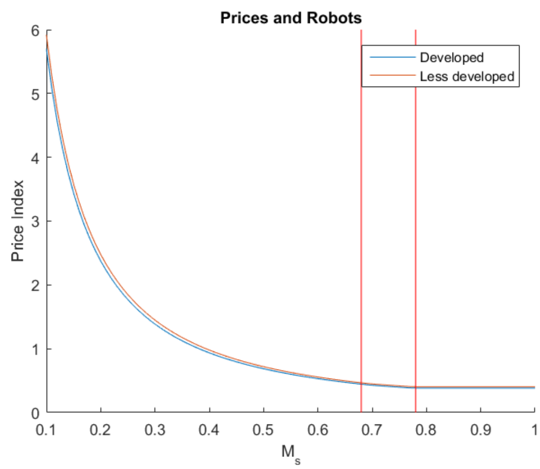
$$\kappa_{jh,s} = \left[M_{js,h}^{\epsilon} q_h^{1-\epsilon} + (1-M_{js,h})^{\epsilon}\left(\frac{w_{j,h}}{\gamma_{js,h}}\right)^{1-\epsilon}\right]^{\frac{1}{1-\epsilon}}$$

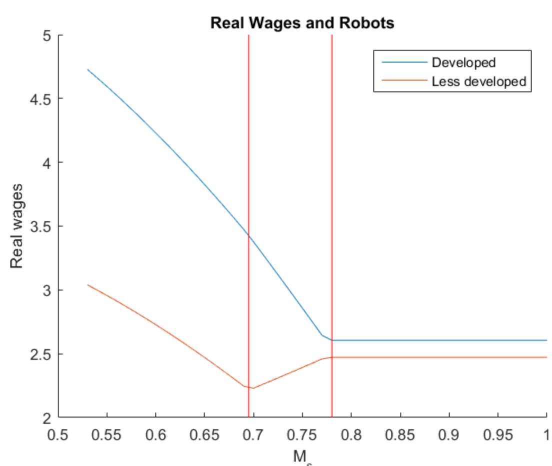
$$p_{jj,s} = \frac{1}{A_{js}}\left(\theta_{js}\kappa_{jl,s}^{1-\rho_s} + (1-\theta_{js})\kappa_{jj,s}^{1-\rho_s}\right)^{\frac{1}{1-\rho_s}}$$

## Simulation

We first simulate this model with two countries, one sector and only low skilled workers. For now we assume that the world supply of robots is perfectly inelastic equals to $\bar{R} = 100$. We assume the following parametrization $\epsilon = 3$, $\sigma = 2$, $\gamma_d = \gamma_u = 1$, $A(d) = 3$, $A(u) = 1$, we set $q = 1$, and $M_s$ changes from 0.5 to 1, to see how robots adoption adjust after this global technological shock:

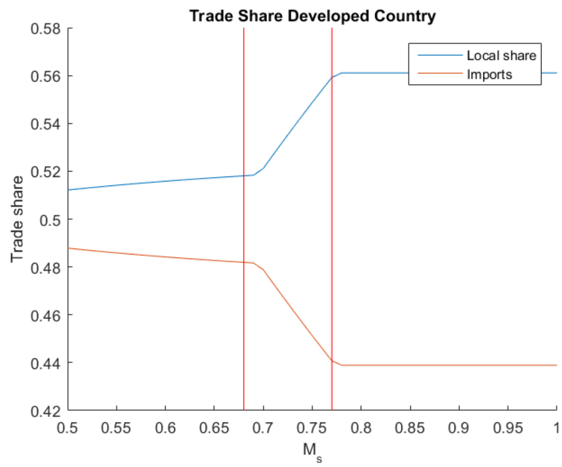


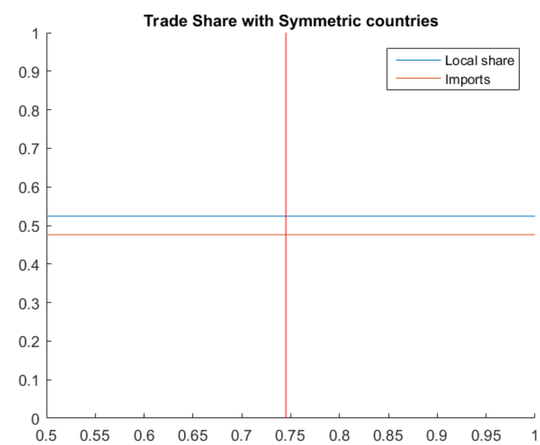



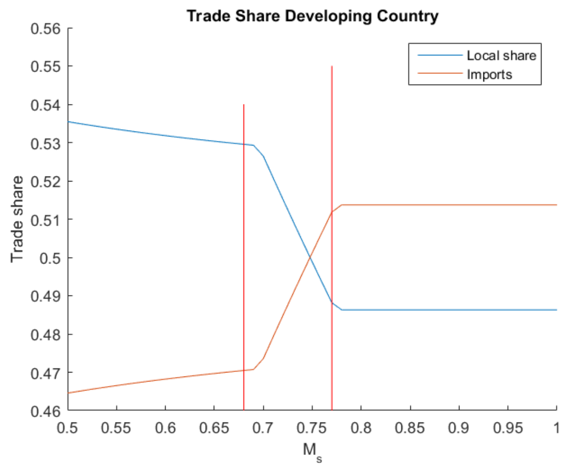

From the figures, we can see that wages decrease as there are more tasks that can be produced by robots. We can also see that prices decrease with more automation, so if we consider real wages, less developed countries actually benefit when they are not restricted, while less developed countries always reduce there real wages.

The next figures show what happens with trade share in the developed country after the development of technology. We can see that this country will reduce its imports and increase its local share, as now that country can develop those tasks cheaper. This pattern is not presented when we have symmetrical countries as we can see in the next figures:




In the case of the developing country, it increases its share of imports, as the price of the foreign good decreases:



Trade Share Developing Country
Local share
Imports
Trade share
0.56
0.55
0.54
0.53
0.52
0.51
0.5
0.49
0.48
0.47
0.46
0.5
0.55
0.6
0.65
0.7
0.75
0.8
0.85
0.9
0.95
1
$M_s$