Universidad de San Andrés

Departamento de Economía

Maestría en Economía

Robots and Offshoring

Gastón NIEVAS OFFIDANI

DNI 37552189

Mentor: Marisol RODRIGUEZ CHATRUC

Buenos Aires

26 de septiembre, 2019

Tesis de Maestría en Economía de

Gastón NIEVAS OFFIDANI

"Robots y Offshoring"

Resumen: Analizamos el impacto del aumento de la robotización en la industria manufacturera sobre el *offshoring*, definido como la participación de bienes intermedios importados. Construimos un panel de 71 países y siete sectores manufactureros para el período 1993-2015 usando datos del stock de robots y del comercio de bienes intermedios. Encontramos que los sectores que experimentan un incremento en la densidad de robots presentan un crecimiento menor del offshoring. Curiosamente, el efecto es mayor para el comercio entre países desarrollados y la mayoría del efecto ocurrió antes de la crisis financiera global, por lo que no encontramos evidencia de que la robotización sea responsable del lento crecimiento del offshoring posterior a la crisis. Es importante resaltar que los resultados no están impulsados por la industria automotriz.

Palabras clave: Densidad de robots, automatización, offshoring, manufacturas, comercio de bienes intermedios.

"Robots and Offshoring"

Abstract We examine the impact of increased robotization in manufacturing on offshoring, defined as the share of imported intermediate inputs. We construct a panel dataset of 71 countries and seven manufacturing sectors for the period 1993-2015 using data on robot stocks and on intermediate goods' trade. We find that sectors that experienced increased robot densification, experienced slower offshoring growth. Interestingly, the effect is stronger for trade within developed countries and most of the effect took place before the global financial crisis, so we do not find evidence that robotization is responsible for the post-crisis sluggish growth in offshoring. Importantly, results are not driven by the auto industry.

Keywords: Robot density, automatization, offshoring, manufacturing, intermediate goods' trade.

Códigos JEL: F1, O30, O4

1 Introduction

The increasing ability of robots to perform tasks previously performed by humans is transforming the manufacturing industry around the world. Robots were already widely employed in the OECD countries' automotive industry since the 1980s, but in recent years they spread to other industries and to emerging countries. This expansion was facilitated by an expansion of robots' capabilities–robots are now able to perform tasks like welding, painting, and packaging–as well as by a marked decline in their prices. There is widespread concern about the impacts on the economy of the transformations brought by robots–as well as by other related technologies, such as 3D printing or Artificial Intelligence–. Most of the debates and analyses focus on the direct impact that robot adoption can have on productivity and on the labor market by replacing workers (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2019).

However, robotization can also affect the economy *indirectly*, through international trade. In the past two decades global production became increasingly fragmented, with countries specializing in different stages of production and the offshoring of tasks becoming increasingly relevant (Hummels, Ishii, and Yi, 2001; Johnson and Noguera, 2012). This process was arguably facilitated by the massive decrease in communication costs brought by ICTs (Baldwin and Martin, 1999; Baldwin and Venables, 2013; Fort, 2017). With increased automation, the cost advantage of offshoring certain tasks could vanish, leading to a decrease in trade in intermediates globally.

In this paper, we exploit variation in the adoption of robots across countries and sectors, to explore if robot densification–i.e. an increase in the number of robots per worker–has negatively impacted offshoring, defined following Feenstra and Hanson (1999) as an industry's share of imported inputs. To this end, we construct measures of offshoring and robot density for a panel of 71 countries and seven manufacturing sectors for the period 1993-2015 using data from the International Federation of Robotics (IFR) and from the Eora Multi-Region Input Output Matrix.

Identifying causal effects in this context is challenging since there can be omitted factors varying at the country and sector level that affect offshoring, such as organizational or management changes, or the adoption of other technologies, that we do not observe. In addition, there could be reverse causality emerging from shocks to offshoring that lead to increased robot adoption as a defensive response. To deal with these issues, we adopt an instrumental variable approach. We use a shift share instrument defined as the change in aggregate robot density within countries for 1993–2015 times the initial share of the world robot density in the sector. We also use variation across sectors in the degree of *replaceability* of human tasks by robots, as defined in Graetz and Michaels (2018) to instrument for changes in robot density, which leads to qualitatively similar results.

We estimate a negative impact of robotization on offshoring over the 1993–2015 period. Given that we use variation at the country and sector level and that offshoring showed an upward trend during our sample period, our results can be interpreted in the following way: country-sector pairs that experienced larger increases in robot density, experienced as a consequence slower offshoring growth. More precisely, moving a country-sector pair from the lowest to the highest percentile of changes in robot density, implies an annual average decrease in offshoring of 2.62 over the 1993-2015. We interpret this results as indicative that the adoption of robots induces the substitution of tasks produced domestically for imported tasks. Our results are robust to the inclusion of country and sector trends as well as other controls, such as changes in wages and in tariffs. Importantly, we check that our results are not driven by the transport equipment sector, which is the sector that accounts for the largest share of robots in the world.

In addition, we decompose our measure of offshoring into within and between sector offshoring to determine if the substitution of tasks happens within the same sector or across sectors. Within sector offshoring corresponds to the definition of narrow offshoring by Feenstra and Hanson (1999) and is equal to the share of imported inputs from the same sector of destination while between-sector offshoring corresponds to the difference between total offshoring and within offshoring. We find results to be similar across both definitions of offshoring, but more precisely estimated for between offshoring.

We also explore heterogeneity across levels of development of both importing and exporting countries. We find the negative impact of robot density on offshoring takes places across all levels of development but tends to be higher for trade flows occurring between developed countries. Although this might seem contrary to intuition –it is expected that developed countries will show a higher replacement on imports from developing countries–, it is consistent with the evidence on the impact of ICTs on fragmentation provided in Fort (2017). She finds that high technology industries are more likely to source from high human capital countries.

Our paper speaks to the literature that studies the relationship between trade and technology. Several papers explore the impact that trade shocks have on technology adoption. Bloom, Draca, and Van Reenen (2016) and Bernard et al. (2018) find evidence in favor of trade-induced technical change, Bustos (2011) reaches similar conclusions studying the MERCOSUR impact on Argentinian firms, Dorn et al. (2016) find a negative relationship between import competition and innovation and, similarly, Pierce and Schott (2018) findings suggest that exposure to an increase in import competition reflects in relative declines in investment in the industry. A related set of papers explores the other direction of causality–from technological change to trade–. Fort (2017) finds that a firm's adoption of communication technology is associated with an increase in its probability of fragmentation. Steinwender (2018) estimates that that the introduction of the transatlantic telegraph generated an efficiency gain in trade between the United States and the United Kingdom equivalent to 8 percent of export value. We contribute to this literature by studying how an automation technology like robots can impact the fragmentation of production.

The two most closely related papers to ours are De Backer et al. (2018) and Artuc, Bastos, and Rijkers (2018). These authors in independent research also explore the relationship between robot adoption and international trade. First, De Backer et al. (2018) estimate the impact of the growth of the robot stock on several outcomes such as offshoring, forward linkages, and backward linkages. Our study complements De Backer et al. because it examines a longer period (1993-2015 vs. 2000-2015). We also use robot density instead of robot stock, to account for the disparities relative to the size of countries, and a more demanding specification along with an instrumental variable approach to address the potential endogeneity of this robot density. Second, Artuc, Bastos, and Rijkers (2018) estimate the impact of an increase in robotization in the north on trade with the south. Our study is different in that it incorporates robotization in the south as well as north-north and south-south trade in the analysis and uses data on imports by the industry that is automating and not aggregate country-level imports as in Artuc et al. (2018). Our data allows us to study a bigger sample of countries (71 vs 24).

Our paper also contributes to the small but growing literature that estimates the impacts of robotization in the economy. Graetz and Michaels (2018) find that increased robot use contributes to annual labor productivity growth, while raising total factor productivity and lowering output prices. Acemoglu and Restrepo (2019) present evidence that suggests that the introduction of robots may reduce employment and wages. A related set of papers studies the determinants of robot adoption (Abeliansky and Prettner (2017) and Acemoglu and Restrepo (2018) associate demographic change–lower population growth/aging–to greater adoption of automation technologies, including robots, leading to more robotics-related activities.

The paper is organized as follows. Section 2 states our empirical strategy, section 3 describes data sources and shows descriptive statistics, and section 4 presents the results of our estimation. Finally, section 5 concludes.

2 Empirical strategy

We empirically examine the impact that increased robot density has had on offshoring, using variation in changes in robot density across sectors and countries. Our baseline specification is:

$$\Delta \ln \mathit{Offshoring}_{cs} = \beta f(\Delta RD_{cs}) + \gamma \mathit{Controls}_{cs} + \delta_c + \psi_s + \varepsilon_{cs} \tag{1}$$

where the difference operator refers to changes between 1993 and 2015. $\mathit{Offshoring}_{cs}$ is the share of imported intermediate inputs in total (manufactured) intermediate inputs demand in country c and sector s.[1] RD_{cs} is the robot density in country c and sector s, which is equal to the ratio of the robot stock per thousand of workers. $f(x)$ is a function where percentiles are calculated upon the distribution of changes in robot density, taking into account weights, as in Graetz and Michaels (2018). These weights are based on the share of country–industry employment in each country's total employment for the year 1990. Since the number of workers can respond endogenously to changes in other variables in the model, when we calculate the long difference of offshoring, we keep employment fixed at its 1990 value, this is: $\Delta RD_{cs} = \frac{RD_{cs,2015} - RD_{cs,1993}}{L_{cs,1990}}$. We also include control variables ($\mathit{Controls}_{cs}$) that vary at the country and sector level, such as changes in tariffs and wages. Since the model is in differences, country and sector effects are differenced out. However, we include country and sector fixed effects in our baseline model to account for country and sector trends. In all our specifications we cluster standard errors by country i.

The intuition behind our specification is the following. Sector s in country i imports a share of its manufacturing inputs from other countries, this is what we call offshoring.

[1] We follow the definition of outsourcing by Feenstra and Hanson (1999) but we call it offshoring since outsourcing can occur within national borders but offshoring is the type of outsourcing that takes place across national borders.

A fall in robot prices will induce the substitution of robots for workers in some country-sector cells, given that robots can perform tasks previously performed by workers but at a cheaper price. Some of these tasks are embedded in imported inputs. Therefore, an increase in robotization can induce some industries to locally produce parts that were previously imported, reducing the degree of offshoring.

Our baseline specification faces some challenges for the identification of the casual effect of robotization on offshoring. First, we make certain assumptions about depreciation and imputations to the robot data, as described in section 3.1 that could generate measurement error. This can compound with the fact that we estimate our model in changes, generating an attenuation bias. Second, omitted variables that vary at the country and sector level could cause bias in any direction. Third, an important source of concern is the potential reverse causality between robotization and trade. More precisely, we cannot rule out that the decision to acquire robots is not taken as a response to a decrease in offshoring caused by something else, such as a shock to offshoring costs.[2]

To address this possible sources of endogeneity, we use an instrumental variables approach. We use a shift share instrument defined as the change in aggregate robot density within countries for 1993–2015 times the initial share of the world robot density in the sector. We also perform robustness checks using a different instrument, *replaceability* of human tasks by robots as defined in Graetz and Michaels (2018).

Our main identification strategy is a Bartik shift share instrument proposed in Graetz and Michaels (2018). This instrument is constructed calculating the change in aggregate robot density from 1993–2015 for each country, and the global robot density in 1993 for each industry. Then, both measures are multiplied and we computed the percentile rank of the product weighted by 1990 within-country employment shares, exactly as with the dependent variable.

The other instrumental strategies tested is an industry-level measure of *replaceability* defined in Graetz and Michaels (2018). This instrument measures how likely it is that an occupation from the 1980 US Census will be replaced by robots. To do so, we checked if the 2000 Census three-digit occupations included in its name any of the applications the IFR distinguishes among robots. If they match, the occupation is giving a replaceability

[2]As mentioned in the introduction, there is evidence that suggests that technology adoption could be affected through different channels and in different directions by trade fluctuations. (Bernard et al. (2018), Bloom, Draca, and Van Reenen (2016), Bustos (2011), Dorn et al. (2016), Fort (2017), Pierce and Schott (2018), Steinwender (2018)).

value of one. We then need to compare the 2000's occupations with the 1980 ones. This is possible using the 1990 Census occupational classification as an intermediate step, given that is also provided for both the 1980 and 2000 censuses. There are some cases where different 2000 occupations map into the same 1990 occupation. The later will be consider as replaceable if at least one of the 2000 occupations mapping is considered as replaceable. Next, these variables are assigned to each individual in the 1980 IPUMS Census based on their reported 1990 occupation. According to their occupation and the 1990 Census industry classification, each individual is assigned an Eora MRIO industry[3]. Finally, the sum product of replaceability and annual hours worked is divided by the total sum of hours worked (applying individual weights in the 1980 IPUMS Census). An important thing to take into account is that this means occupations are classified as replaceable even if only part of their work can be done by robots and not the whole. In other words, the replaceability values represent an upper bound to the share of hours where work may be done by robots.

Our first stage is therefore:

$$f(\Delta RD_{cs}) = \quad \alpha Z_{cs} + \omega Controls_{cs} + \chi_c + \rho_s + \zeta_o + \nu_{cs} \tag{2}$$

3 Data and descriptive evidence

3.1 Data sources

To estimate the impact of robotization on offshoring, we combine data from the International Federation of Robotics (IFR), the Eora MRIO, and UNIDO.

We rely on IFR for data on the stock and on the incorporations of industrial robots by 4-digit ISIC revision 4 industry, country and year. The data comprises 6 sectors–with the manufacturing sector being the only sector desagregated into 11 industries– and 75 countries for the period 1993–2015, but with gaps.[4] According to IFR, a robot is "an

[3]To make this conversion we had to map the 1990 Census industry classification with EU KLEMS industries first. Then the concordance EU KLEMS - Eora was done. See Appendix B Table 9.

[4]As data on robot stock is not specified by industry for several countries in early years, imputations at the industry-level is needed. Another limitation of the data comes from the North American region as up to 2011 Canada, Mexico, and the US were combined in a single reported stock. Imputations at the country-level for the pre-2011 period is therefore needed. Values are calculated using post-2011 shares. We describe how we perform imputations in Appendix A. In addition, due to inconsistencies in the stock of robots as a result of reclassifications, we also drop Japan from our sample. We also check that our main

actuated mechanism programmable in two or more axes with a degree of autonomy, moving within its environment, to perform intended tasks." (International Federation of Robotics (2017)), where autonomy refers to the ability to perform tasks without human intervention. The IFR then distinguishes between two types of robots, according to their intended application: service robots [5] and industrial robots. As the quality of data on service robots is not the best and our study focuses in manufacturing industries, we only use the industrial robots data which, naturally, are the ones used in industrial automation application. IFR constructs the stock of robots by compiling information reported by robot suppliers as well as from national robot associations and assumes that the robot stock does not depreciate yearly but instead depreciates entirely in the twelfth year after acquisition. Instead, we use a more realistic yearly depreciation rate of 10 percent.[6]

To obtain data on offshoring, we rely on the Eora Multi-regional Input Output Matrix (Eora MRIO) in its 26-sector version (Eora 26), which is available for 189 countries annually for the period 1990-2015.[7] The number of countries as well as the period spanned makes Eora much more complete than other databases. [8]

We obtain industry-level employment and wage data from United Nations Industrial Development Organization (INDSTAT2 (2017)). This dataset spans 171 countries for the period 1963-2016, with some gaps.[9]

Finally, we use tariffs from a joint CESIfo Group-World Bank effort following the methodology of Felbermayr, Teti, and Yalcin (2018).

The robot and offshoring data are at different industry classifications so we construct a correspondence between the classifications in IFR and in Eora (see Table 7 in Appendix

results still hold when we use raw IFR data without performing any imputations.

[5]A service robot is a "robot that performs useful tasks for humans or equipment excluding industrial automation application."

[6]The same approach is used by Graetz and Michaels (2018)

[7]See Lenzen et al. (2012) and Lenzen et al. (2013) for details on the construction of this database.

[8]The IO tables are constructed using a variety of sources of data, which makes it quite reliable. The sources are: (1) input–output tables and production data from national statistical offices; (2) IO from Eurostat, IDE-JETRO, and OECD; (3) the UN National Accounts Main Aggregates Database; (4) the UN National Accounts Official Data; (5) the UN Comtrade international trade database; and (6) the UN Service Trade Statistics Database.

[9]Some data at the INDSTAT2 level is missing. In order to solve this problem we came up with a two step solution: for the cases where the data was available at the INDSTAT4 level, the aggregated values was used to fill in the blanks. If this data was also missing, imputations of the country-industry employment were made by filling in with the previous value available. We describe how we perform imputations in Appendix A.

B), which yields seven sectors. The same process is done to match the employment and offshoring data (see Table 8 in Appendix B). The final product is a database with the data at the Eora industry classification level. In addition, Eora covers 189 countries whereas IFR covers 75 countries. We only consider in our regressions 71 of the 75 countries in IFR, however, we use the remaining countries in EORA to obtain imports for those 71 countries (see Table 10 Appendix C for a list of countries). As a consequence, our dataset covers 71 countries and 7 manufacturing sectors for the 1993–2015 period. [10]

3.2 Descriptive evidence

As mentioned in section 3.1, we focus on the impact of robot adoption on offshoring across 71 countries in seven manufacturing sectors. By the end of 2015, the worldwide robot stock in manufacturing accounted for 1,140,000 units [11], with Asia and Pacific being the region with the largest share of the world's stock, even when we exclude Japan. At the region's top of our sample of countries, China holds 161,430 robots, followed by South Korea with 130,967. Only four countries in the world have a stock of more than 100,000 robots, and two of them belong to Asia and Pacific. The other two are United States (126,173) and Germany (115,878).

There are 41 Non-OECD countries in our final data, with a mean robot density of 0.97 and a maximum of 5.64, corresponding to Czech Republic, as shown in Table 11. The remaining 30 OECD countries have an average of 6.87 robots per thousand workers, with a maximum of 22.79 corresponding to Korea. See Figure 1.

The global robot stock has been steadily increasing since 1993, driven initially by OECD countries.[12] In the Non-OECD group of countries growth in the robot stock has spurred after 2009, led by China. The postcrisis period has encourage less developed countries to adopt a higher amount of robots. In 2009, of a total of 537,740 robots, only 5.9 percent were owned by Non-OECD countries whereas at the end of year 2015 they

[10]The countries used in the study do not include Japan, North Korea, Uzbekistan and Puerto Rico. The first one is excluded because its data presents some inconsistencies throughout time due to reclassification of robots within the country. Given that the UNIDO dataset does not include data for North Korea and Uzbekistan, computing the robot density for these countries was not possible. Finally, Puerto Rico does not appear in the Eora dataset, so we have no idea of its offshoring for the period studied.

[11]This number include all the 75 countries of the IFR database, although we already explained why we don't use in our regressions Japan, North Korea, Uzbekistan and Puerto Rico.

[12]We do not include Mexico and Chile in the OECD countries'group. We consider both countries Non-OECD countries to keep all Latin America and Caribbean countries in the same group.

held 21.6 percent of the global stock. Figure 2 reflects how this impacted on the robot density by type of country.

The auto industry has experienced an early automation since the 1980s, being now the sector with the highest amount of robots and, consequently, with the biggest robot density as shown in Figure 3. Although the sectoral automation ranking behaves almost the same comparing OECD and Non-OECD countries, the latter group has more Textiles and Wearing Apparel robots than Wood and Paper ones, as shown in Figure 9. Explained by the fact their economies have developed this sector relatively more. Still, it is almost nothing comparing with other sectors. This shows one of the challenges robotization is trying to surpass: there are some tasks in which it is still hard to replace human labor with the current available technology and many of those belong to work in the textiles sector.

When it comes to our dependent variables, Broad and Narrow Offshoring, the evidence shows an increasing trend for the period of study -Figure 5-. This changes when we analyze each sector separately, as in Figure 6, where Electrical and Machinery, Transport Equipment, Petroleum Chemical and Non-Metallic Mineral Products and Metal Products are the sectors with offshoring levels lower than the ones at the beginning of the period. Again, disparities are found when taking into account the type of country that is experiencing the automation. As shown in Figures 7 and 8, Non-OECD countries are experiencing a decreased in offshoring whereas OECD countries' trend is increasing.

4 Estimation results

In order to examine the impact of robotization on offshoring we present and analyze the results of our a baseline model in section 4.1, then we move on to heterogeneous effects across different exporting and exporting regions in section 4.2, and finally, we perform robustness exercises in section 4.3.

4.1 Baseline results

We present our core estimates in Table 1. The first fourth columns show OLS estimates including country and sector trends and controls for changes in wages and in tariffs in a sequential manner. The most demanding specification in the fourth column yields an estimate of −0.21 (column 4), somewhat larger in magnitude than the ones corresponding to specifications that do not include sector trends in the first and second column.

To address the potential endogeneity of changes in the robot density (explained in section 2), we present in the fifth to seventh columns of Table 1 2SLS estimates. The fifth column shows that when using replaceability–as calculated in Graetz and Michaels (2018)–as an instrument the point estimate decreases somewhat in magnitude to −0.36 and is less precise. One disadvantage of this instrument is that it only uses variation at the sector level, so in the sixth and seventh columns we report results using a shift-share instrument, that allows to control for both country and sector trends. When we only include country trends and controls, this instrument yields an estimate (column 6) that is closer to OLS than the one in the fifth column. However, when we control in addition for sector trends, the estimate is markedly higher, with a value of −0.86 (column 7).

There are at least two potential explanations to the fact that OLS estimates are smaller than IV estimates. The first one is attenuation bias stemming from measurement error in robot adoption which can be due to the fact that we calculate robot densities by imputing data for some countries and years or to the fact that variation in robot stocks does not necessarily reflect differences in robot capabilities and quality across sectors and countries. The second are unobserved shocks to foreign productivity that lead to an increase in the share of imported intermediates but also to domestic technical change. For example, Bloom, Draca, and Van Reenen (2016) find evidence for Europe that offshoring to China increases domestic IT intensity and productivity. This correlation between unobserved shocks and robot adoption biases the (negative) OLS estimates upwards and therefore, makes the estimated effect of the increase robot density on offshoring smaller in absolute value than what it truly is.

Even though point estimates vary to some extent across specifications and methods, the results in Table 1 unambiguously point to increases in robot adoption being related to reductions in offshoring. The 2SLS estimates range from −0.36 (column 5) to −0.86 (column 7), which amounts, respectively, to a decrease in offshoring of 1.35 to 2.62 percent per year on average for a country-sector pair that moves from the lowest to the highest percentile of changes in robot density, during the 1993–2015 period.[13]

[13]The values come from applying the formula $100 \times e^{\hat{\beta}-1}/22$, where 22 is the number of years elapsed between 1993 and 2015.

4.2 Heterogeneous effects

In the previous subsection we estimated the overall impact that robot densification has on offshoring, but how does this impact vary across countries or sectors? In this section we explore these issues.

First, we examine the varying effects of robotization across countries of different levels of development. To this end, we construct the dependent variable distinguishing if the country sourcing the imports (i.e. the partner country) is developed (OECD) or developing (non-OECD). Therefore, for each country-sector pair, we have two observations for offshoring, one corresponding to the share of imported inputs from OECD countries and the other to the share of imported inputs from non-OECD countries that we stack in a single regression. Both values add up to offshoring as defined in section 4.1. In addition, we can also distinguish for each of the (importing or reporter) countries if they belong to the OECD or not. This yields the following estimating equation:

$$
\begin{aligned}
\Delta \ln Off^{o}_{cs} = \quad & \beta_{11} f(\Delta RD_{cs}) \times \text{OECD}_c \times \text{OECD}_o + \beta_{12} f(\Delta RD_{cs}) \times \text{OECD}_c \times \text{Non-OECD}_o \\
& + \beta_{13} f(\Delta RD_{cs}) \times \text{Non-OECD}_c \times \text{OECD}_o \\
& + \beta_{14} f(\Delta RD_{cs}) \times \text{Non-OECD}_c \times \text{Non-OECD}_o \\
& + \gamma_1 Controls_{cs} + \delta_{1,c} + \psi_{1,s} + \xi_{1,o} + \varepsilon_{1,cs}
\end{aligned} \tag{3}
$$

where $o = \{\text{OECD,Non-OECD}\}$ is the region that is the origin of the imports, $OECD_c$ and $Non-OECD_c$ are , respectively, indicator variables equal to one if the importing country belongs to the OECD or not, $OECD_o$ and $Non-OECD_o$ are indicator variables equal to one if the origin of the imports is the OECD or not, respectively, and ξ_o is an origin-region fixed effect.

We instrument each interaction with the interaction of the instrument and the corresponding dummies. Therefore the first stage corresponding to equation 3 is:

$$
\begin{aligned}
f(\Delta RD_{cs}) = \quad & \alpha_{11} Z_{cs} \times \text{OECD}_c \times \text{OECD}_o + \alpha_{12} Z_{cs} \times \text{OECD}_c \times \text{Non-OECD}_o \\
& + \alpha_{13} Z_{cs} \times \text{Non-OECD}_c \times \text{OECD}_o \\
& + \alpha_{14} Z_{cs} \times \text{Non-OECD}_c \times \text{Non-OECD}_o \\
& + \omega_1 Controls_{cs} + \chi_{1,c} + \rho_{1,s} + \zeta_{1,o} + \nu_{1,cs}
\end{aligned}
\tag{4}
$$

where Z_{cs} is the instrumental variable.

We report results from the estimation of equation 3 in Table 2. The first fourth columns show OLS estimates including country and sector trends and controls for changes in wages and in tariffs in a sequential manner. The point estimates are negative across all combinations of reporters and partners, but are somewhat larger in absolute value for the pairs that correspond to OECD reporters and partners. In the most demanding specification in the fourth column the only coefficients that remain significant are the ones corresponding to an OECD partner (i.e. exporter). In addition, in this specification the effects are more negative for combinations of OECD reporter-OECD partner followed by combinations of Non-OECD reporter-OECD partner. When using the shift-share instrument as an IV for robot densification, we find that all four point estimates are negative. As mentioned above, we have some concerns when introducing the sector fixed effects in the 2SLS estimation, where the coefficients increase in a considerable amount, a problem that does not occur when accounting only for country fixed effects. As in OLS, this specification has the biggest effect for the pair OECD reporter-OECD partner when controlling only for country trends. However, when sector fixed effects are included the largest coefficient corresponds to the pair OECD reporter-Non-OECD partner. When using repleaceabilty, point estimates remain negative but the one corresponding to OECD reporter-OECD partner is the largest in absolute value and is more precisely estimated than the rest (column 5). As this instrument varies at the sector level only, we can not control for sector trends so we do not experience the same problem as with the shift share.

Second, we examine if robot densification in a country-sector cell has a differential impact on the share of imported intermediates from the same sector (within-sector offshoring) than on the share of imported intermediates from other sectors (between-sector offshoring). To this end, we decompose offshoring into the share of intermediate imports from the same sector that is importing them and the share of intermediates from sectors other than the importing sector. Within-sector offshoring corresponds to what Feenstra and Hanson (1999) denominate *narrow* offshoring and the definition we used in the baseline estimation (see section 4.1) corresponds to what they call *broad* offshoring.[14] The sum of within-sector (or narrow) offshoring and between sector offshoring adds up to broad offshoring. We stack both measures of offshoring in a single regression, which means that for every country-sector change in robot density we have two observations of offshoring, doubling the number of observations from the value we have in the baseline. We estimate the following:

$$\begin{aligned} \Delta \ln Off^{w}_{cs} = \quad & \beta_{21} f(\Delta RD_{cs}) \times \text{Within}_s + \beta_{22} f(\Delta RD_{cs}) \times \text{Between}_s \\ & + \gamma_2 Controls_{cs} + \delta_{2,c} + \psi_{2,s} + \xi_{2,w} + \varepsilon_{2,cs} \end{aligned} \tag{5}$$

where w = {within,between} is the type of offshoring, $Within_s$ and $Between_s$ are, respectively, indicator variables equal to one depending to which offshoring is being tested and ξ_w is a fixed effect that accounts for the offshoring type.

As in the previous exercise, we instrument each interaction with the interaction of the instrument and the corresponding dummies. Therefore the first stage corresponding to equation 5 is:

$$\begin{aligned} f(\Delta RD_{cs}) = \quad & \alpha_{21} Z_{cs} \times \text{Within}_s + \alpha_{22} Z_{cs} \times \text{Between}_s \\ & + \omega_2 Controls_{cs} + \chi_{2,c} + \rho_{2,s} + \zeta_{2,w} + \nu_{2,cs} \end{aligned} \tag{6}$$

Results for within and between-sector offshoring are shown in Table 3. The first to fourth columns display OLS estimates. For the most demanding specification in the fourth column, the estimated coefficients for within-sector and between-sector offshoring are similar in magnitude and in precision. When using as an IV the interaction between replaceability and the dummies for within and between sector offshoring, the point estimate is larger for between-sector offshoring and imprecise for within sector offshoring. However, when using the interaction between the shift-share instrument and the dummies for within and between sector offshoring, the opposite happens: the coefficient for within-sector is larger and relatively more precise. Given that OLS and both IVs yield conflicting results, we remain agnostic about any differential effect for

[14] See also Wright (2014).

within and between sector offshoring.

4.3 Robustness exercises

We perform a series of robustness exercises to verify the validity of our study. To our discontent, we were not able to run a placebo test similar to the one in Graetz and Michaels (2018) due to the lack of observations before our sample period.

4.3.1 Alternative definitions of Robot Density

The missing data for some specific sectors, countries or years obliged us to perform a series of imputations. To check whether this imputations are biasing the results or not we contrast different definitions of robot density with our baseline model. The results shown in Table 6 allow us to determine that the conclusions are robust to different ways of using the data.

4.3.2 Pre and Post Crisis

Our period of study includes the financial crisis of 2008, which certainly led to lower levels of worldwide trade. To exclude the crisis effect from our analysis we divide the time period in two: Pre-crisis 1993-2007 and Post-crisis 2010-2015, see Table 4. For the pre-crisis period we encounter that results behave in the same way as before, maintaining the negativity and significance. However, we find that for the post crisis period the estimates lose significance in the most exigent OLS regressions. Even more, the sign of the replaceablity instrument is positive in this case. These findings suggest that most of the effect of automation over offshoring took place before the crisis. There is no enough evidence to extract conclusions for the years after the crisis.

4.3.3 No Transport equipment

We were particularly concerned about the high concentration of robots in the Transport equipment industry, as displayed in several figures. An important result we found is that, when taking Transport equipment out from the sample, results hold. Table 5 shows that point estimates behave accordingly with the previous results. We conclude that, regardless of the disparity in the adoption of robots among sectors, the decrease of offshoring caused by automation is not only a phenomenon of the auto industry but it happens across manufacturing sectors.

5 Conclusion

There is widespread concern about the effects of new technologies such as robots, artificial intelligence, and 3D printing in the economy. These technologies have the potential to boost productivity but also to displace workers along the way. Most of the analyses focus on the effects of automation of domestic industries on domestic employment. However, the effects of automation can be felt even if domestic industries do not automatize, through the automation of trade partners. In the past decades, global production has become increasingly fragmented, with countries specializing in producing certain tasks leading to an expansion in intermediate goods' trade. When a certain industry in a country automatizes, it can start producing certain tasks domestically, decreasing its offshoring of tasks to other countries. This reduces demand for intermediate goods in those countries and can have negative consequences for workers in those economies, even if they do not automatize.

In this paper, we explored how robot adoption affects offshoring, and therefore, international trade in intermediate goods. To this end, we built a panel dataset of seventy-one countries and seven manufacturing sectors for the period 1993-2015 that contains information on offshoring–defined as the share of manufactured intermediate inputs– and on the robot stocks. To address endogeneity concerns we used an instrumental variable approach, a shift share variable that interacts the change in aggregate robot density within countries with the global share of each industry at the beginning of the period. We also used an alternative instrument based on the variation across industries in the replaceability of humans by robots (Graetz and Michaels (2018)).

We find that industry-country pairs that increase their robot adoption relatively more, experience a decrease in offshoring. Given that during our sample period offshoring was on an upward trend, our results imply that increases in robotization lead to lower offshoring growth. We also find that these effects behave differently when taking into account North-North, North-South, South-North and South-South trade. We don't see any differential effect regarding within and between offshoring. The results remain robust to different ways of defining robot density, not considering the years of the financial crisis or taking out the Automotive sector from the sample.

Our results point to the importance of considering the automation of trade partners when evaluating the effects on new technologies in the economy. Even if a country is not undergoing a process of automation, the increasing trend of world's adoption of robots could affect its trade patterns.

References

Abeliansky, Ana and Klaus Prettner. 2017. "Automation and demographic change." *Available at SSRN 2959977* .

Acemoglu, Daron and Pascual Restrepo. 2018. "Demographics and automation."

———. 2019. "Robots and jobs: Evidence from US labor markets." *Journal of Political Economy, forthcoming* .

Artuc, Erhan, Paulo Bastos, and Bob Rijkers. 2018. "Robots, Tasks and Trade." The World Bank Policy Research Working Paper # 8674.

Baldwin, Richard and Anthony J. Venables. 2013. "Spiders and snakes: Offshoring and agglomeration in the global economy." *Journal of International Economics* 90 (2):245–254.

Baldwin, Richard E. and Philippe Martin. 1999. "Two waves of globalisation: Superficial similarities, fundamental differences." NBER Working Paper # 6904.

Bernard, Andrew B, Teresa C Fort, Valerie Smeets, and Frederic Warzynski. 2018. "Heterogeneous globalization: Offshoring and reorganization." Tech. rep., Working paper.

Bloom, Nicholas, Mirko Draca, and John Van Reenen. 2016. "Trade induced technical change? The impact of Chinese imports on innovation, IT and productivity." *The Review of Economic Studies* 83 (1):87–117.

Bustos, Paula. 2011. "Trade liberalization, exports, and technology upgrading: Evidence on the impact of MERCOSUR on Argentinian firms." *American economic review* 101 (1):304–40.

De Backer, Koen, Timothy DeStefano, Carlo Menon, and Jung Ran Suh. 2018. "Industrial robotics and the global organisation of production."

Dorn, David, Gordon H Hanson, Gary Pisano, Pian Shu et al. 2016. "Foreign competition and domestic innovation: Evidence from US patents." Tech. rep., National Bureau of Economic Research.

Feenstra, Robert C. and Gordon H. Hanson. 1999. "The impact of outsourcing and high-technology capital on wages: estimates for the United States, 1979–1990." *The Quarterly Journal of Economics* 114 (3):907–940.

Felbermayr, Gabriel J, Feodora Teti, and Erdal Yalcin. 2018. "On the profitability of trade deflection and the need for rules of origin." .

Fort, Teresa C. 2017. "Technology and production fragmentation: Domestic versus foreign sourcing." *The Review of Economic Studies* 84 (2):650–687.

Graetz, Georg and Guy Michaels. 2018. "Robots at work." *Review of Economics and Statistics* 100 (5):753–768.

Hummels, David, Jun Ishii, and Kei-Mu Yi. 2001. "The nature and growth of vertical specialization in world trade." *Journal of international Economics* 54 (1):75–96.

INDSTAT2, UNIDO. 2017. "INDSTAT 2 Industrial Statistics Database at 2-digit level of ISIC Revision 3." *Vienna* .

International Federation of Robotics. 2017. "World Robotics Industrial Robots 2017." Tech. rep.

Johnson, Robert C. and Guillermo Noguera. 2012. "Accounting for intermediates: Production sharing and trade in value added." *Journal of international Economics* 86 (2):224–236.

Lenzen, Manfred, Keiichiro Kanemoto, Daniel Moran, and Arne Geschke. 2012. "Mapping the structure of the world economy." *Environmental science & technology* 46 (15):8374–8381.

Lenzen, Manfred, Daniel Moran, Keiichiro Kanemoto, and Arne Geschke. 2013. "Building Eora: A global multi-region input–output database at high country and sector resolution." *Economic Systems Research* 25 (1):20–49.

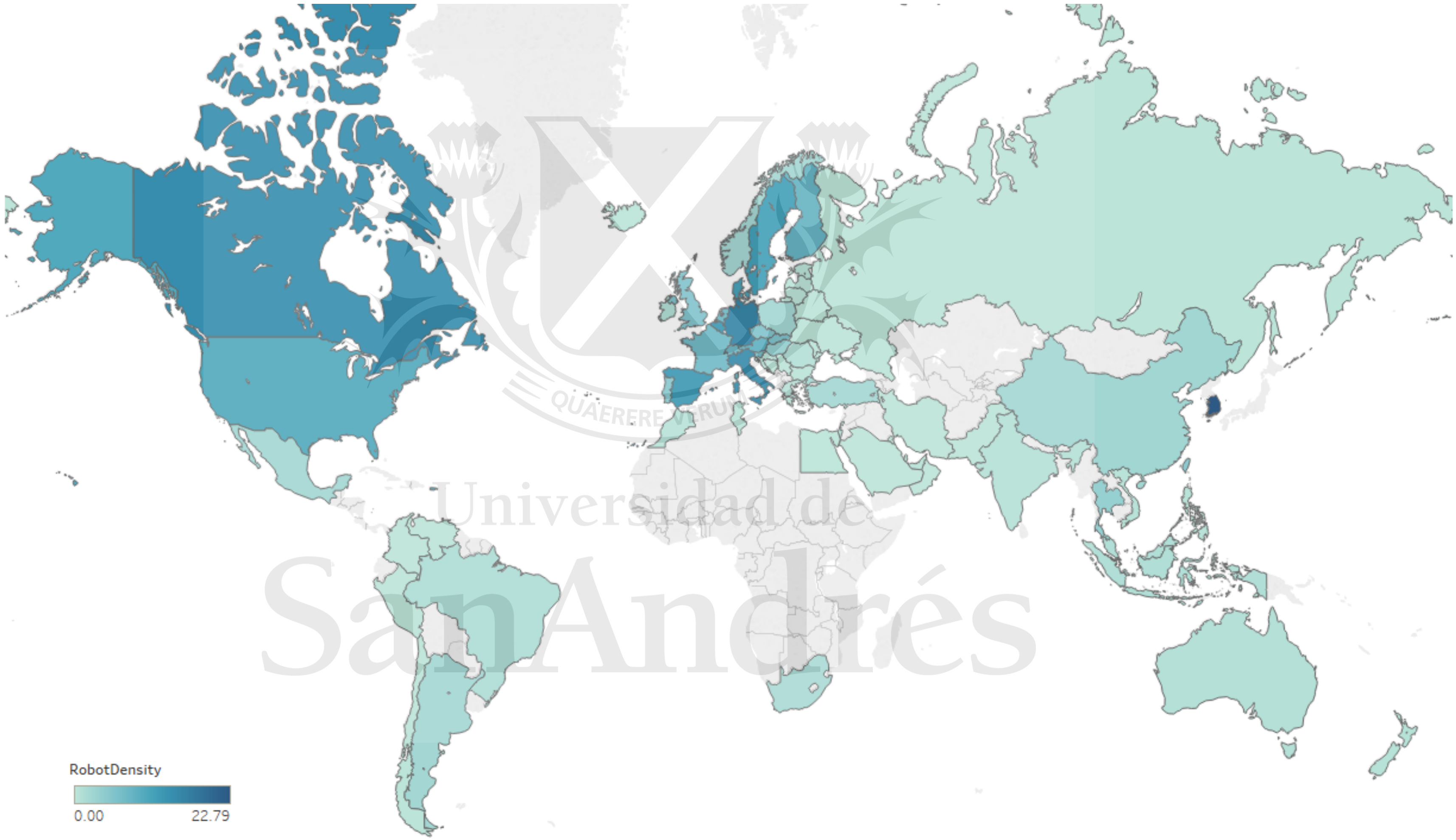
Pierce, Justin R and Peter K Schott. 2018. "Investment responses to trade liberalization: Evidence from US industries and establishments." *Journal of International Economics* 115:203–222.

Steinwender, Claudia. 2018. "Real effects of information frictions: When the states and the kingdom became united." *American Economic Review* 108 (3):657–96.

Wright, Greg C. 2014. "Revisiting the employment impact of offshoring." *European Economic Review* 66:63–83.

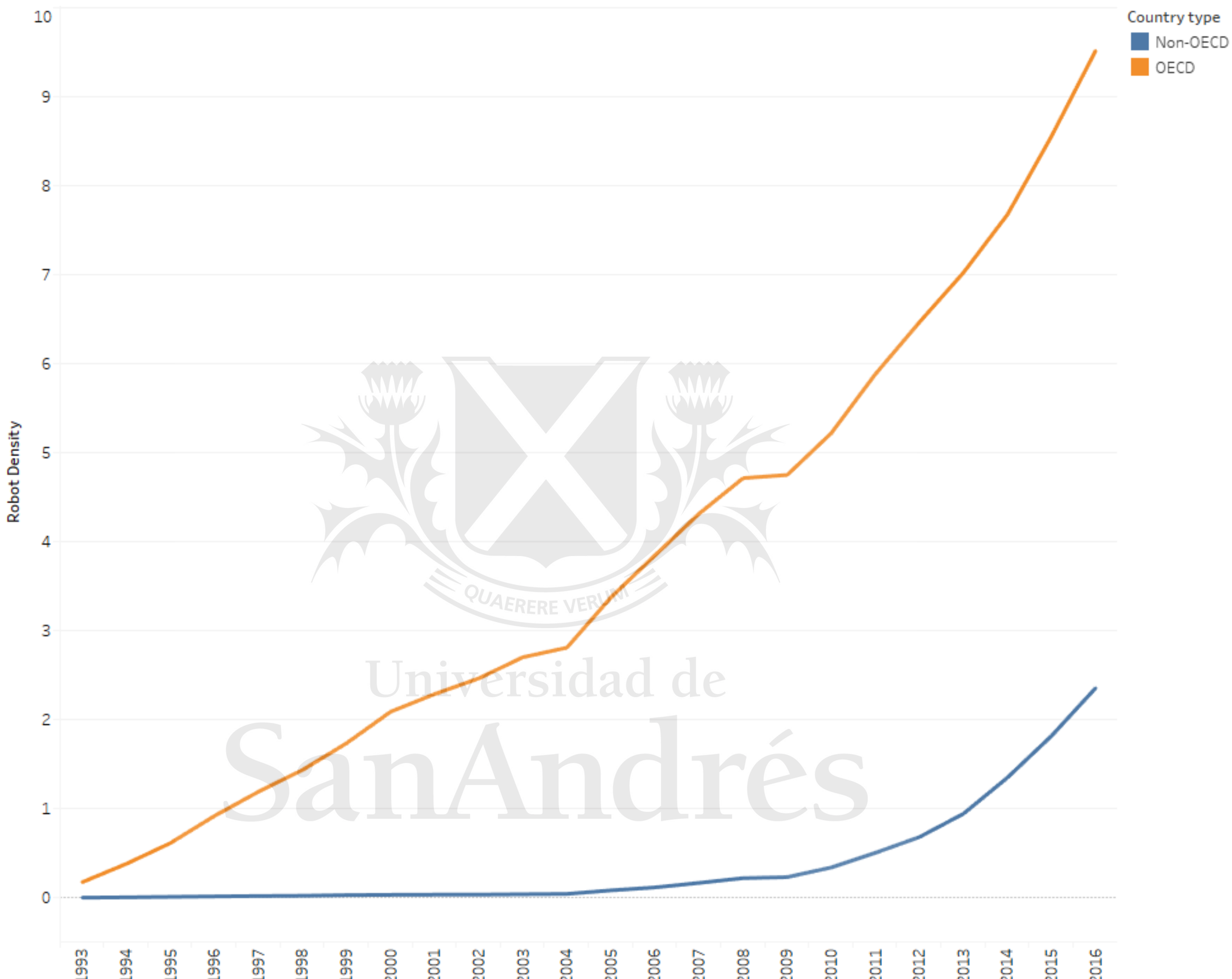
6 Figures

Figure 1: Robot density, 2015



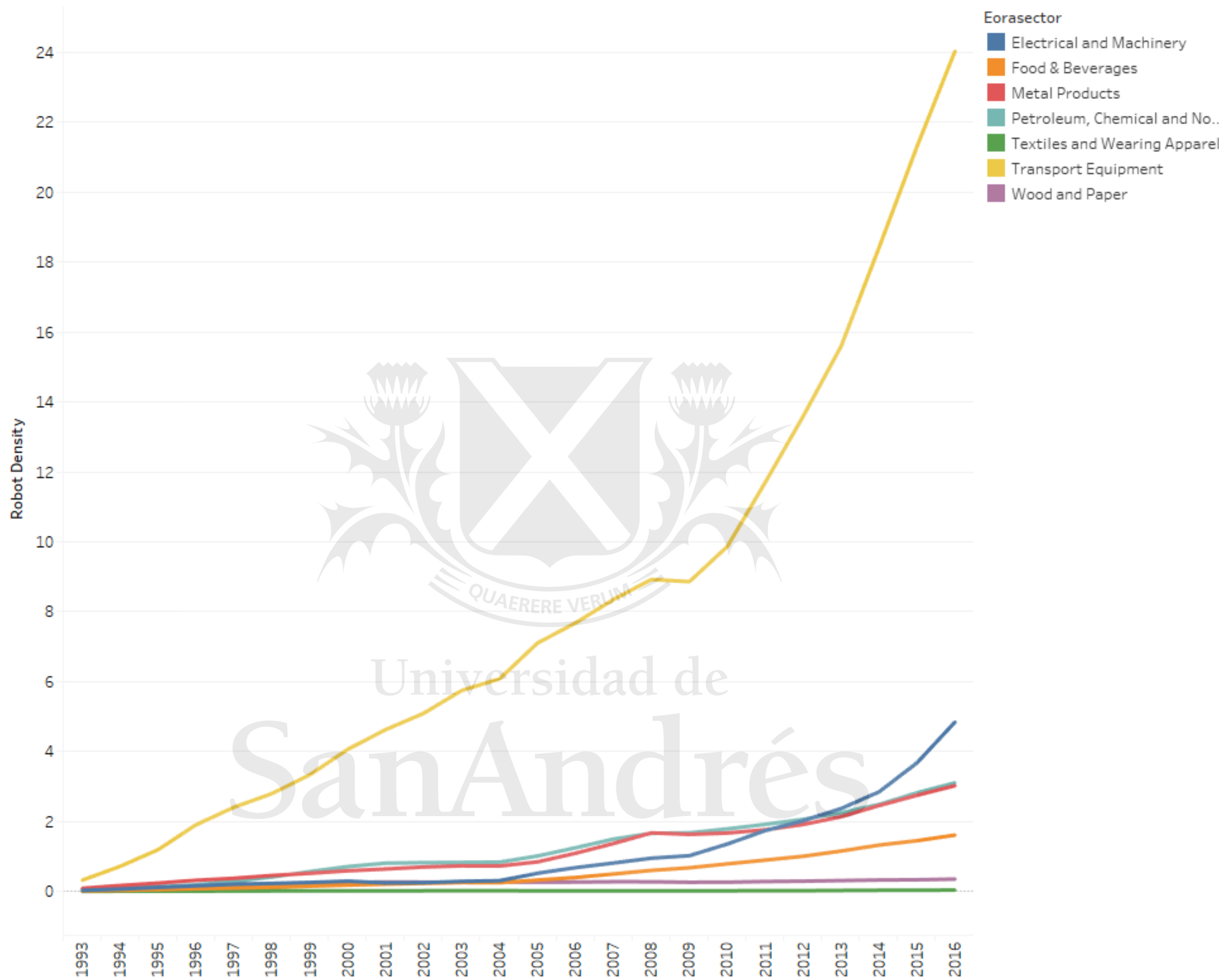
Note: Map shows the manufacturing robot density for the year 2015. Robots data comes from the IFR, assuming a yearly robot depreciation rate of 10%. Employment data comes from UNIDO. Darker colors show a bigger robot density.

Figure 2: Evolution of the Robot Density by type of country



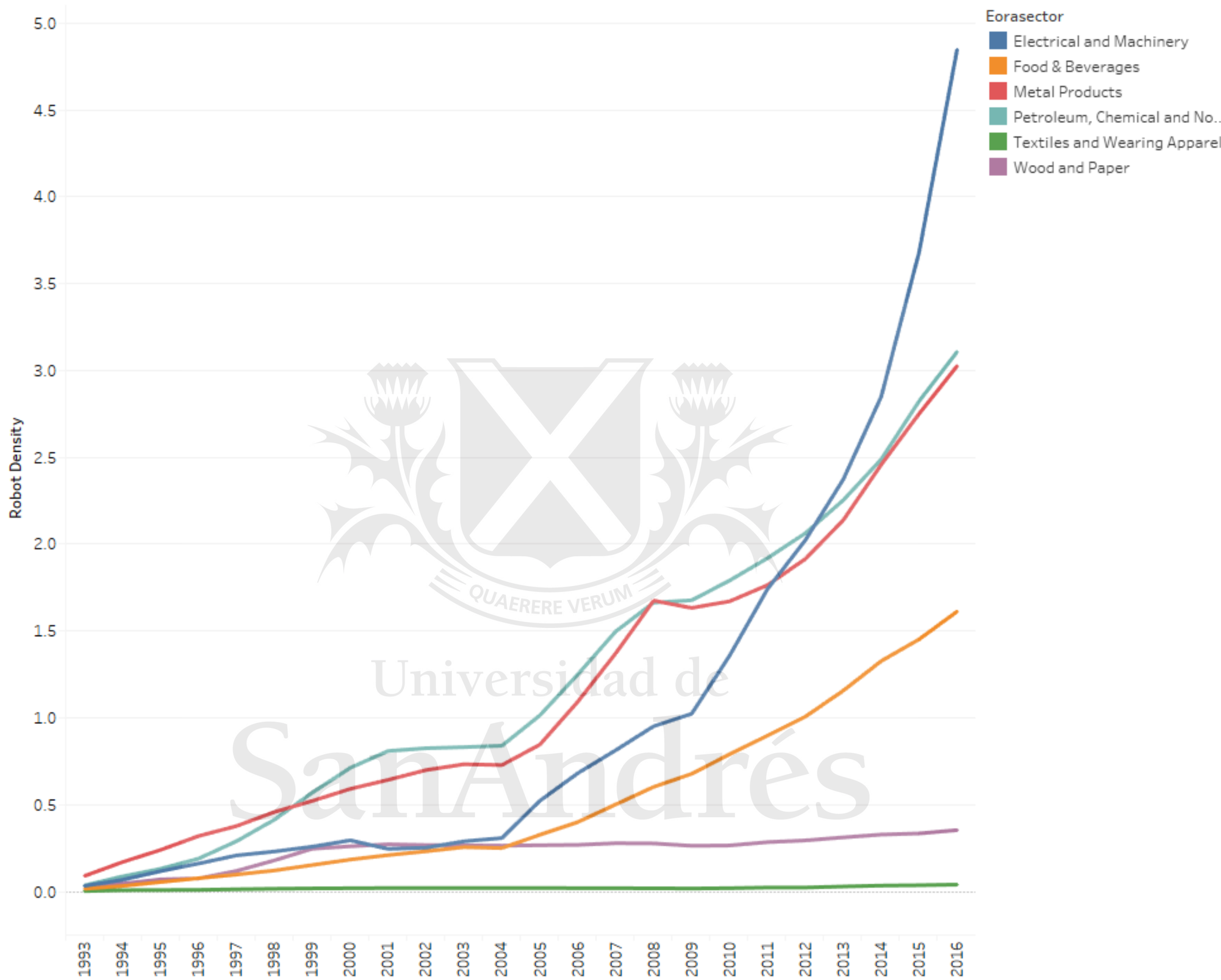
Note: Time series for the weighted average of Robot Density by type of country. Robots data comes from the IFR, assuming a yearly robot depreciation rate of 10%. Employment data comes from UNIDO.

Figure 3: Evolution of Robot Density by sector



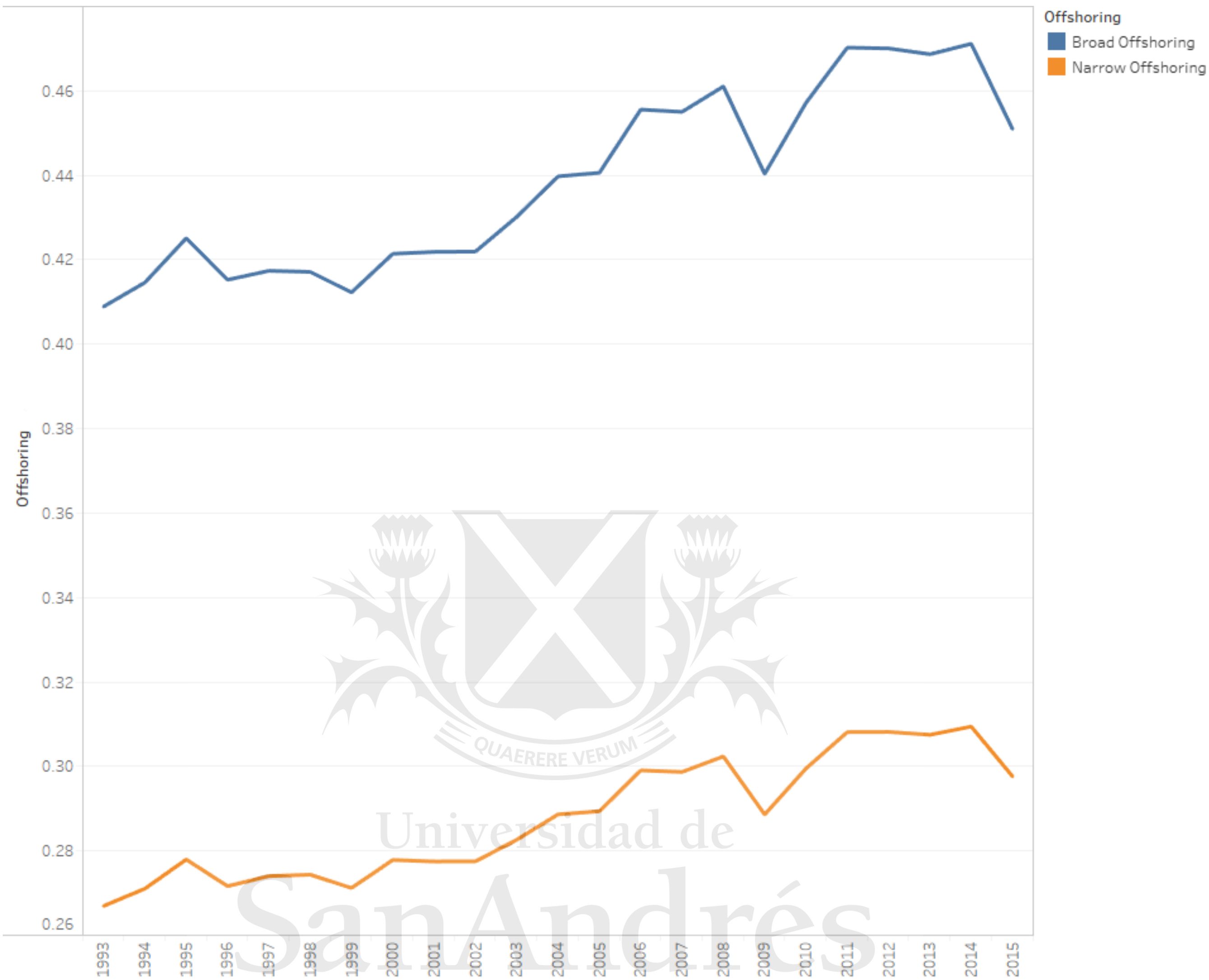
Note: Time series for the weighted average of Robot Density by sector. Robots data comes from the IFR, assuming a yearly robot depreciation rate of 10%. Employment data comes from UNIDO.

Figure 4: Evolution of Robot Density by sector without Transport Equipment



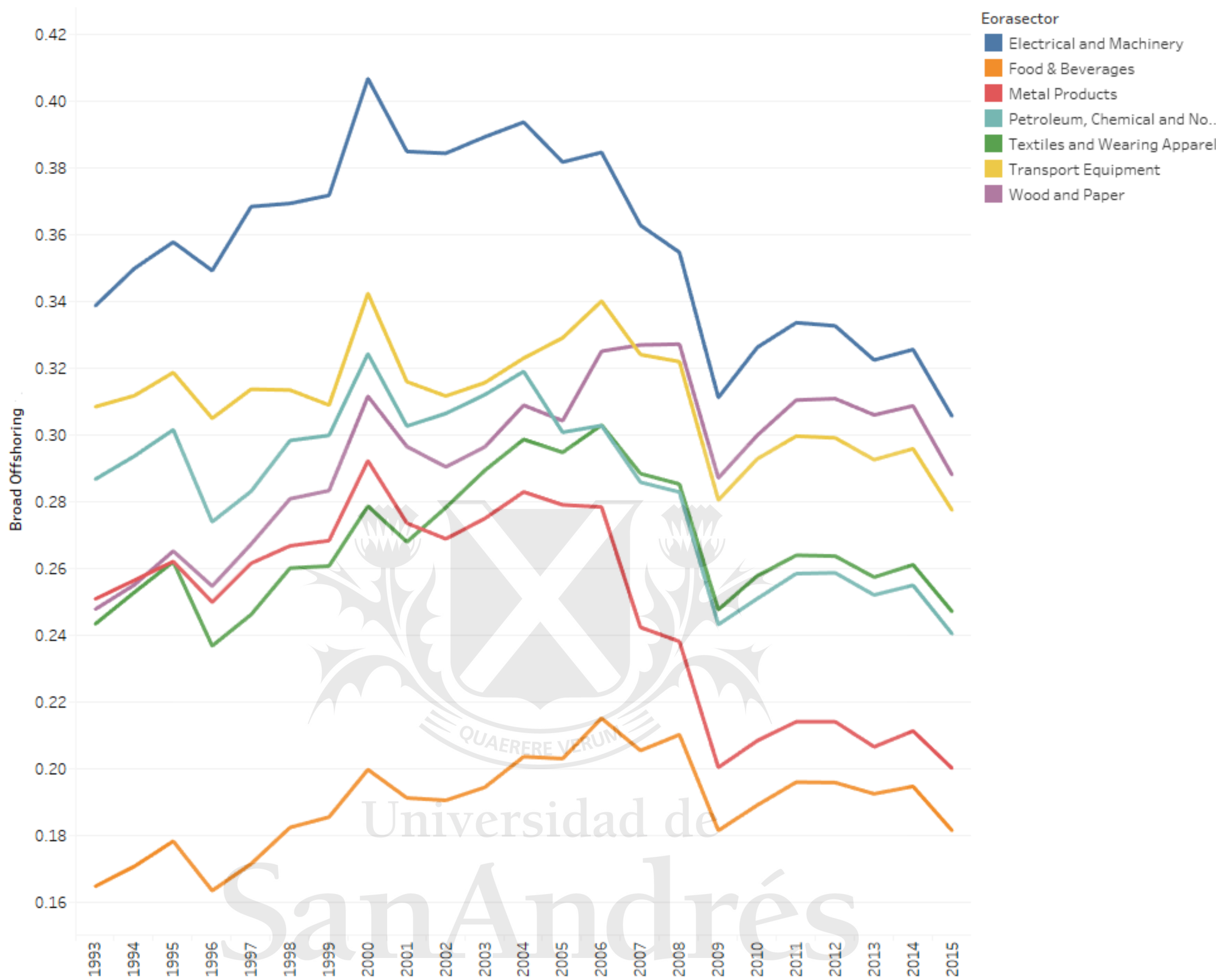
Note: Time series for the weighted average of Robot Density by sector, excluding Transport equipment. Robots data comes from the IFR, assuming a yearly robot depreciation rate of 10%. Employment data comes from UNIDO.

Figure 5: Evolution of the total Offshoring



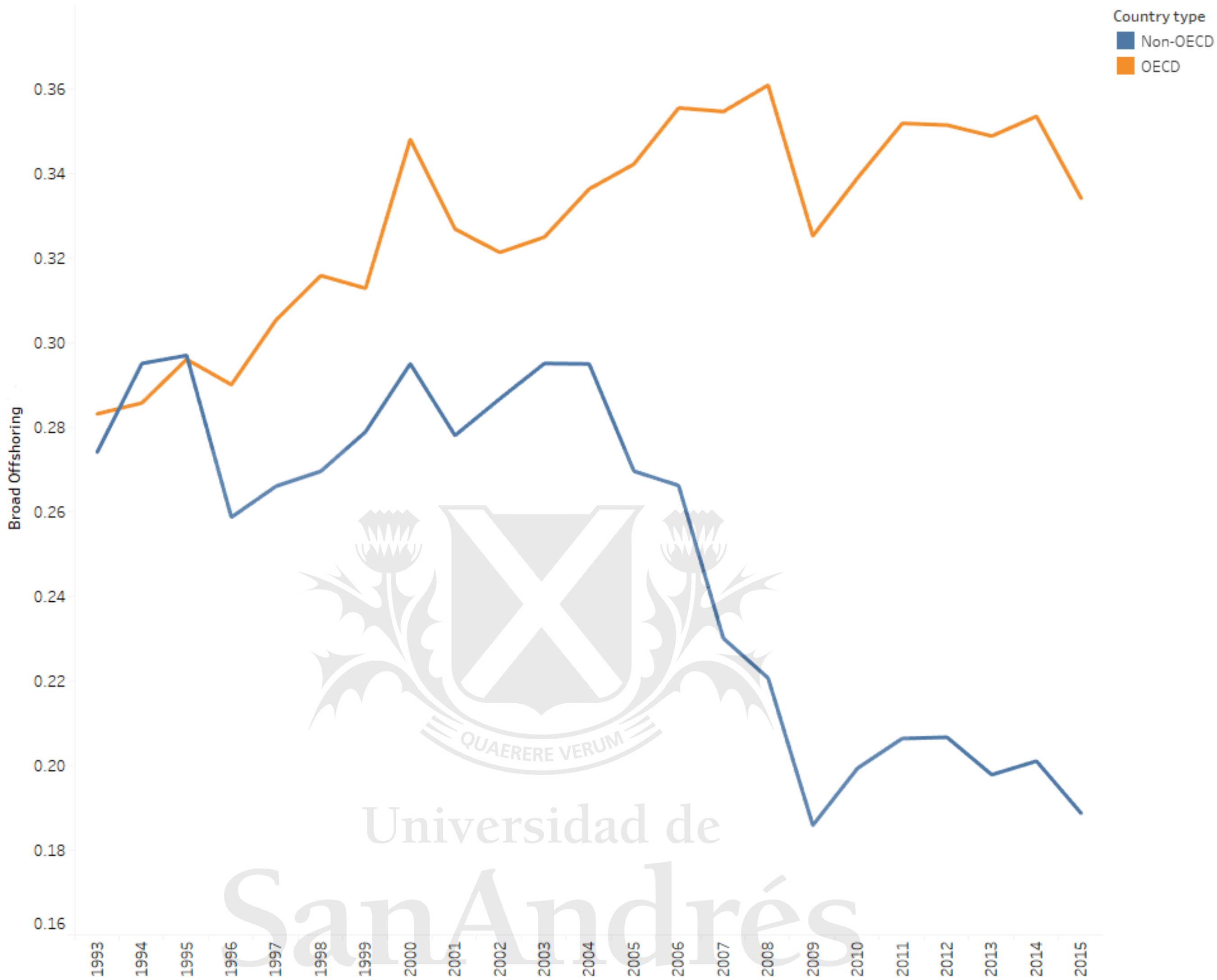
Note: Time series for the weighted average of total offshoring –Broad Offshoring– and within industry offshoring –Narrow Offshoring–. Data comes from EORA.

Figure 6: Evolution of the Broad Offshoring by sector



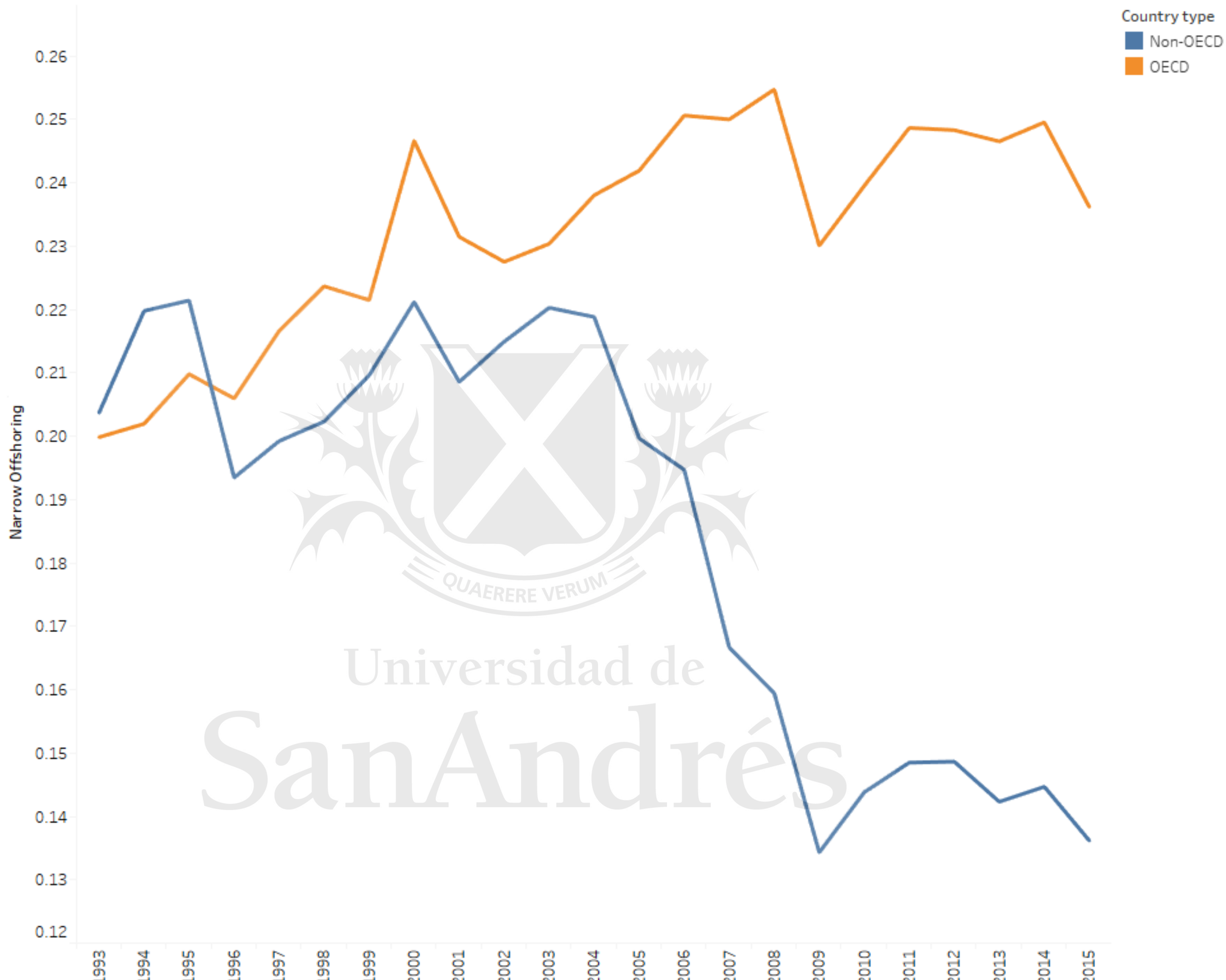
Note: Time series for the weighted average of total offshoring –Broad Offshoring– by sector. Data comes from EORA.

Figure 7: Evolution of Broad Offshoring by type of country



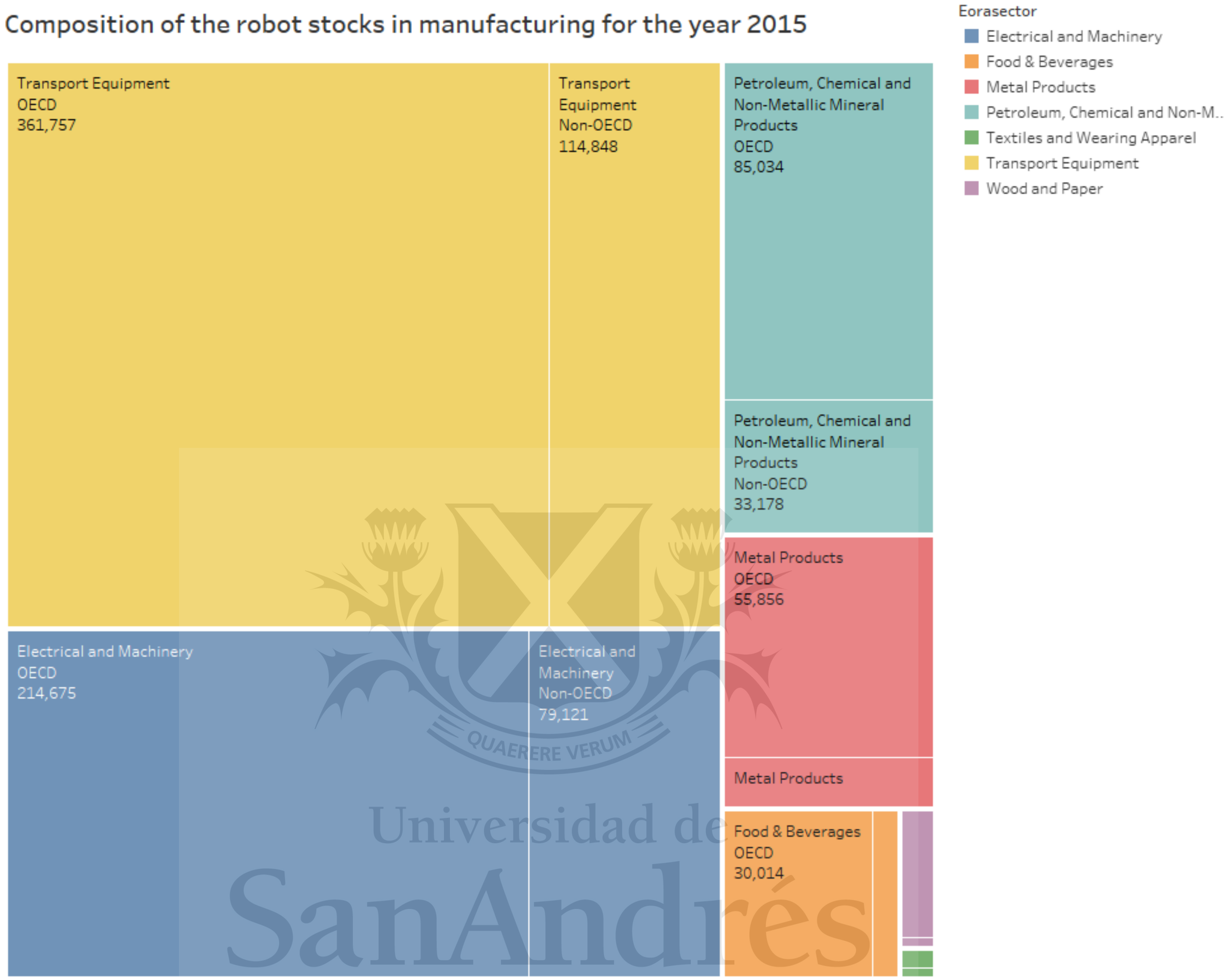
Note: Time series for the weighted average of total offshoring –Broad Offshoring– by type of country. Data comes from EORA.

Figure 8: Evolution of the Narrow Offshoring by type of country



Note: Time series for the weighted average of within offshoring –Narrow Offshoring– by type of country. Data comes from EORA.

Figure 9: Stock per industry



7 Tables

Table 1: The impact of robot densification on offshoring. Baseline estimates.

	OLS				2SLS		
					Replaceab	Shift-share	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$f(\Delta RD_{cs})$	-0.165***	-0.180***	-0.214***	-0.212***	-0.355**	-0.286***	-0.860***
	(0.0517)	(0.0542)	(0.0709)	(0.0719)	(0.163)	(0.0785)	(0.303)
Country trends	✓	✓	✓	✓	✓	✓	✓
Sector trends			✓	✓			✓
Controls		✓		✓	✓	✓	✓
Observations	497	483	497	483	483	483	483
R-squared	0.791	0.783	0.799	0.791	0.774	0.780	0.734
F-statistic					73.51	232.5	70.20

The table shows OLS (columns 1–4) and 2SLS (columns 5–7) estimates of a model in long differences (1993–2015) where the dependent variable is the logarithmic difference of offshoring, defined as the share of imported manufacturing inputs, and the independent is the percentiles of the change in robot density. Percentiles are calculated upon the distribution of changes in robot density, taking into account weights. These weights are based on the share of country-industry employment in each country's total employment for the year 1990, which is the year we used in our definition of robot density. Both variables are at the country (N=71) and sector (N=7) level. Controls included are the logarithmic change (between 1993 and 2015) of wages in manufacturing and of one plus the tariff rate. The number of observations decreases when we include controls due to missing values in those variables. The instruments are replaceability, defined as in Graetz and Michaels (2018) and a shift-share corresponding to the initial share of the world robot density in the sector times the change in the country-level robot density. All regressions are weighted by the same weight we used to calculate percentiles, as in Graetz and Michaels (2018).
Standard errors are clustered by country. (***) $p < 0.01$, (**) $p < 0.05$, (*) $p < 0.1$.

Table 2: Heterogeneous effects. OECD and Non-OECD trade.

			OLS				2SLS		
							Replaceab	Shift-share	
			(1)	(2)	(3)	(4)	(5)	(6)	(7)
$f(\Delta RD_{cs})$	OECD reporter	OECD partner	-0.106	-0.109	-0.253**	-0.241**	-0.439**	-0.223**	-0.903***
			(0.0736)	(0.0743)	(0.107)	(0.109)	(0.173)	(0.104)	(0.340)
		Non-OECD partner	-0.103	-0.106	-0.156	-0.148	-0.191	-0.211*	-0.947**
			(0.0924)	(0.0935)	(0.137)	(0.140)	(0.204)	(0.126)	(0.388)
	Non-OECD reporter	OECD partner	-0.109	-0.130*	-0.213**	-0.211**	-0.299	-0.0487	-0.692**
			(0.0745)	(0.0774)	(0.0816)	(0.0815)	(0.273)	(0.127)	(0.313)
		Non-OECD partner	-0.0884	-0.0930	-0.144	-0.134	-0.259	-0.174	-0.862**
			(0.0775)	(0.0817)	(0.0904)	(0.0911)	(0.322)	(0.130)	(0.365)
Country trends			✓	✓	✓	✓	✓	✓	✓
Partner trends			✓	✓	✓	✓	✓	✓	✓
Sector trends					✓	✓			✓
Controls				✓		✓	✓	✓	✓
Observations			994	966	994	966	966	966	966
R-squared			0.879	0.877	0.885	0.883	0.872	0.876	0.856

The table shows OLS (columns 1–4) and 2SLS (columns 5–7) estimates of a model in long differences (1993–2015) where the dependent variable is the logarithmic difference of offshoring, defined as the share of imported manufacturing inputs, and the independent is the percentiles of the change in robot density. Percentiles are calculated upon the distribution of changes in robot density, taking into account weights. These weights are based on the share of country-industry employment in each country's total employment for the year 1990, which is the year we used in our definition of robot density. Both variables are at the country (N=71) and sector (N=7) level. Controls included are the logarithmic change (between 1993 and 2015) of wages in manufacturing and of one plus the tariff rate. The number of observations decreases when we include controls due to missing values in those variables. The instruments are replaceability, defined as in Graetz and Michaels (2018) and a shift-share corresponding to the initial share of the world robot density in the sector times the change in the country-level robot density. All regressions are weighted by the same weight we used to calculate percentiles, as in Graetz and Michaels (2018). Variables are interacted with dummies of OECD and Non-OECD reporter/partner. Partner trends controls for the type of origin country.

Standard errors are clustered by country. (***) $p < 0.01$, (**) $p < 0.05$, (*) $p < 0.1$.

Table 3: Heterogeneous effects. Within and Between Offshoring.

		OLS				2SLS		
						Replaceab	Shift-share	
		(1)	(2)	(3)	(4)	(5)	(6)	(7)
$f(\Delta RD_{cs})$	Within-industry	-0.114*	-0.133**	-0.226***	-0.227***	-0.300	-0.222**	-0.991***
		(0.0577)	(0.0595)	(0.0769)	(0.0778)	(0.184)	(0.0893)	(0.344)
	Between-industry	-0.254***	-0.269***	-0.209***	-0.207***	-0.421***	-0.348***	-0.567*
		(0.0575)	(0.0597)	(0.0647)	(0.0655)	(0.157)	(0.0793)	(0.295)
Country trends		✓	✓	✓	✓	✓	✓	✓
Type trends		✓	✓	✓	✓	✓	✓	✓
Sector trends				✓	✓			✓
Controls			✓		✓	✓	✓	✓
Observations		994	966	994	966	966	966	966
R-squared		0.767	0.757	0.778	0.769	0.750	0.755	0.723

The table shows OLS (columns 1–4) and 2SLS (columns 5–7) estimates of a model in long differences (1993–2015) where the dependent variable is the logarithmic difference of offshoring, defined as the share of imported manufacturing inputs, and the independent is the percentiles of the change in robot density. Percentiles are calculated upon the distribution of changes in robot density, taking into account weights. These weights are based on the share of country-industry employment in each country's total employment for the year 1990, which is the year we used in our definition of robot density. Both variables are at the country (N=71) and sector (N=7) level. Controls included are the logarithmic change (between 1993 and 2015) of wages in manufacturing and of one plus the tariff rate. The number of observations decreases when we include controls due to missing values in those variables. The instruments are replaceability, defined as in Graetz and Michaels (2018) and a shift-share corresponding to the initial share of the world robot density in the sector times the change in the country-level robot density. All regressions are weighted by the same weight we used to calculate percentiles, as in Graetz and Michaels (2018). Variables are interacted with dummies of Within and Between Offshoring. Type trends controls for the type of offshoring.

Standard errors are clustered by country. (***) $p < 0.01$, (**) $p < 0.05$, (*) $p < 0.1$.

Table 4: Robustness exercises. No crisis.

	OLS				2SLS		
					Replaceab	Shift-share	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: 2007-1993							
$f(\Delta RD_{cs})$	-0.0959**	-0.106**	-0.0940*	-0.0976*	-0.340**	-0.209***	-0.641***
	(0.0435)	(0.0455)	(0.0538)	(0.0547)	(0.156)	(0.0728)	(0.218)
Observations	497	483	497	483	483	483	483
R-squared	0.789	0.760	0.797	0.770	0.734	0.755	0.691
F-statistic					48.41	211.7	49.65
Panel B: 2015-2010							
$f(\Delta RD_{cs})$	-0.0129**	-0.0100*	-0.0140	-0.0131	0.0347	-0.0229**	-0.0974
	(0.00509)	(0.00599)	(0.0104)	(0.00993)	(0.0373)	(0.0112)	(0.0865)
Observations	497	483	497	483	483	483	483
R-squared	0.812	0.802	0.815	0.805	0.789	0.801	0.771
F-statistic					14.93	150.6	48.69
Country trends	✓	✓	✓	✓	✓	✓	✓
Sector trends			✓	✓			✓
Controls		✓		✓	✓	✓	✓

The table shows OLS (columns 1–4) and 2SLS (columns 5–7) estimates of a model in two long differences, Panel A (1993–2007) and Panel B (2010–2015). The dependent variable is the logarithmic difference of offshoring, defined as the share of imported manufacturing inputs, and the independent is the percentiles of the change in robot density. Percentiles are calculated upon the distribution of changes in robot density, taking into account weights. These weights are based on the share of country-industry employment in each country's total employment for the year 1990, which is the year we used in our definition of robot density. Both variables are at the country (N=71) and sector (N=7) level. Controls included are the logarithmic change of wages in manufacturing and of one plus the tariff rate. The number of observations decreases when we include controls due to missing values in those variables. The instruments are replaceability, defined as in Graetz and Michaels (2018) and a shift-share corresponding to the initial share of the world robot density in the sector times the change in the country-level robot density. All regressions are weighted by the same weight we used to calculate percentiles, as in Graetz and Michaels (2018).
Standard errors are clustered by country. (***) $p < 0.01$, (**) $p < 0.05$, (*) $p < 0.1$.

Table 5: Robustness exercises. No Transport equipment

	OLS				2SLS		
					Replaceab	Shift-share	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$f(\Delta RD_{cs})$	-0.159***	-0.175***	-0.214***	-0.211**	-0.381*	-0.273***	-0.772**
	(0.0584)	(0.0609)	(0.0782)	(0.0800)	(0.198)	(0.0942)	(0.309)
Country trends	✓	✓	✓	✓	✓	✓	✓
Sector trends			✓	✓			✓
Controls		✓		✓	✓	✓	✓
Observations	426	414	426	414	414	414	414
R-squared	0.799	0.792	0.807	0.800	0.781	0.790	0.760
F-statistic					48.37	211.7	69.39

The table shows OLS (columns 1–4) and 2SLS (columns 5–7) estimates of a model in long differences (1993–2015) where the dependent variable is the logarithmic difference of offshoring, defined as the share of imported manufacturing inputs, and the independent is the percentiles of the change in robot density. Percentiles are calculated upon the distribution of changes in robot density, taking into account weights. These weights are based on the share of country-industry employment in each country's total employment for the year 1990, which is the year we used in our definition of robot density. Both variables are at the country (N=71) and sector (N=7) level. Controls included are the logarithmic change (between 1993 and 2015) of wages in manufacturing and of one plus the tariff rate. The number of observations decreases when we include controls due to missing values in those variables. The instruments are replaceability, defined as in Graetz and Michaels (2018) and a shift-share corresponding to the initial share of the world robot density in the sector times the change in the country-level robot density. All regressions are weighted by the same weight we used to calculate percentiles, as in Graetz and Michaels (2018). Transport equipment is excluded from the regressions.
Standard errors are clustered by country. (***) $p < 0.01$, (**) $p < 0.05$, (*) $p < 0.1$.

Table 6: Robustness exercises. Different definitions of robot density

	OLS							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$f(\Delta RD_{cs})$	-0.212***	-0.196***	-0.193***	-0.196***	-0.175**	-0.212***	-0.170***	-0.212***
	(0.0719)	(0.0669)	(0.0725)	(0.0669)	(0.0688)	(0.0717)	(0.0628)	(0.0717)
Country trends	✓	✓	✓	✓	✓	✓	✓	✓
Sector trends	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Yearly depreciation	✓					✓	✓	✓
Imputing unspecified	✓		✓		✓		✓	
Breaking down North America	✓			✓	✓			✓
Observations	483	483	483	478	483	483	483	483
R-squared	0.791	0.783	0.790	0.791	0.789	0.791	0.789	0.791

The table contrasts OLS estimations for the baseline (column 1) with different definitions of robot density (columns 2–8).

Yearly depreciation refers to using a yearly depreciation rate of 10 percent for robot stocks, instead of IFR's approach where robots depreciate entirely after twelve years.

Imputing unspecified refers to when data on robot stock is not specified by industry for several countries in early years and imputations at the industry-level is needed.

Breaking down North America refers to imputations at the country-level for the pre-2011 period for Canada, Mexico and the US, where robot stock was reported under a single value. Values are calculated using post-2011 shares.

Standard errors are clustered by country. (***) $p < 0.01$, (**) $p < 0.05$, (*) $p < 0.1$.

Appendix

A Imputations

A.1 IFR

As we are using a long difference approach, a complication in the analysis was the lack of robot data in the beginning of our period (1993), for the following countries: Australia, Austria, Belgium, Czech Republic, Denmark, Spain, United Kingdom, Hungary, Italy, Rep. of Korea, Netherlands, Poland, Portugal, Russian Federation, Singapore, Slovenia, Taiwan, United States of America. What's more, this data was reported by the IFR but not classified into any industry, the first robots of these countries were labeled as "unspecified". In order to break the data into industries within countries we calculated the share of each country-industry-year robot stock in the total country-year stock (for the years when data was available) and its yearly average. Finally, the product of this average and the "unspecified" stock of robots is what forms the imputed stock.

A similar approach was used to impute the robots in North America for the years previous to 2011. Apart from the lack of industry-level data (solved in the previous paragraph) before 2011 Canada, Mexico and the United States were reported as a sole country. The solution was to compute the share for each country-industry-year in the regional-industry-year stock for the period going from 2011 to 2015. This allowed us to distribute the data between countries, by multiplying the yearly average of this share with the regional-industry-year stock for the first years.

A.2 UNIDO

The INDSTAT2 version of UNIDO dataset presents some gaps in employment values. Although we tried filling this gaps with aggregated data from the INDSTAT4 version, this observations only accounted for 1% of the imputations we needed to perform. To replace the other 99% of missing values, we filled in the country-industry employment using data from the nearest previous year available, as is frequently done.

B Industry correspondence

To simplify our job, we converted all the industry classifications to the one provided by the Eora MRIO. Below we show the concordance tables between Eora and ISIC Rev. 4 (used by IFR), between Eora and ISIC Rev. 3 (used by UNIDO) and between Eora and EU KLEMS.

Table 7: Concordance table between EORA and IFR

EORA sector	**ISIC Rev. 4**	**IFR description**
Food & Beverages	10-12	Food and beverages
Textiles and Wearing Apparel	13-15	Textiles
Wood and Paper	16 17-18	Wood and furniture Paper
Petroleum, Chemical and Non-Metallic Mineral Products	19-22 23	Plastic and chemical products Glass ceramics stone mineral products (non auto)
Metal Products	24 25	Metal - Basic metals Metal - Metal products (non automotive)
Electrical and Machinery	26-27 28	Electrical electronics Metal - Industrial machinery
Transport Equipment	29 30	Automotive Other vehicles

Table 8: Concordance table between EORA and UNIDO

EORA sector	ISIC Rev. 3	ISIC Rev. 3 description
Food & Beverages	15	Manufacture of food products and beverages
	16	Manufacture of tobacco products
Textiles and Wearing Apparel	17	Manufacture of textiles
	18	Manufacture of wearing apparel; dressing and dyeing of fur
	19	Tanning and dressing of leather; manufacture of luggage, handbags, saddlery, harness and footwear
Wood and Paper	20	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials
	21	Manufacture of paper and paper products
	22	Publishing, printing and reproduction of recorded media
Petroleum, Chemical and Non-Metallic Mineral Products	23	Manufacture of coke, refined petroleum products and nuclear fuel
	24	Manufacture of chemicals and chemical products
	25	Manufacture of rubber and plastics products
	26	Manufacture of other non-metallic mineral products
Metal Products	27	Manufacture of basic metals
	28	Manufacture of fabricated metal products, except machinery and equipment
Electrical and Machinery	29	Manufacture of machinery and equipment n.e.c.
	30	Manufacture of office, accounting and computing machinery
	31	Manufacture of electrical machinery and apparatus n.e.c.
	32	Manufacture of radio, television and communication equipment and apparatus
	33	Manufacture of medical, precision and optical instruments, watches and clocks
Transport Equipment	34	Manufacture of motor vehicles, trailers and semi-trailers
	35	Manufacture of other transport equipment

Table 9: Concordance EORA and EU KLEMS

EORA sector	**Industry EU KLEMS**
Food & Beverages	15t16
Textiles and Wearing Apparel	17t19
Wood and Paper	20 21t22
Petroleum, Chemical and Non-Metallic Mineral Products	23t25 26
Metal Products	27t28
Electrical and Machinery Transport Equipment	30t33 34t35

C List of countries

Table 10: List of countries

OECD sample	Non-OECD sample	
Australia	Argentina	Saudi Arabia
Austria	Belarus	Serbia
Belgium	Bosnia-Herzegowina	Singapore
Canada	Brazil	South Africa
Denmark	Bulgaria	Taiwan
Estonia	Chile	Thailand
Finland	China	Tunisia
France	Colombia	Ukraine
Germany	Croatia	United Arab Emirates
Greece	Czech Republic	Venezuela
Hungary	Egypt	Vietnam
Iceland	Hong Kong	
Israel	India	
Italy	Indonesia	
Latvia	Iran	
Lithuania	Ireland	
Netherlands	Kuwait	
New Zealand	Macau	
Norway	Malaysia	
Poland	Malta	
Portugal	Mexico	
Rep. of Korea	Moldova	
Slovakia	Morocco	
Slovenia	Oman	
Spain	Pakistan	
Sweden	Peru	
Switzerland	Philippines	
Turkey	Quatar	
United Kingdom	Romania	
United States	Russian Federation	

D Descriptive stats

Table 11: Robot Density descriptive stats

RobotDensity	max	min	mean	sd	countries
All	22.78634	0	3.477727	4.949143	71
Non-OECD	5.63992	0	.9981884	1.551943	41
OECD	22.78634	.1133257	6.86643	5.935481	30