Robots and re-shoring: Should developing countries start to worry?

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Executive summary

The effects of technological development have become an integral part of economic research. The prediction that technological unemployment would arise due to technological innovation has been made repeatedly in history. However, until now these predictions did not became reality. This is not to say that technologies do not affect the organization of work. In most cases, however, the number of jobs created by new technologies exceeded the number it destroyed. Optimists thus state that, although there can be some initial disruptive effects, market economies are perfectly able to adept to innovation and technological change in the long run and there is no need to worry too much about it. More recently, however, “technological concerns” have been raised once more due to possible links between technology and a number of economic developments that have been observed in recent data. These include: the decline of the labor share, the slowdown of world trade and premature deindustrialization.

Recently, the world started to experience a new wave of automation technologies to emerge, including industrial robots. Industrial robots are not new technology by any means, as the automotive and electronics sectors have been using them for two decades already. However, new technological developments are increasing the capabilities of robots, which allows human labor to be substituted in an ever increasing number of tasks. Industrial robots are therefore expected to impact the future organization of work. Furthermore, data on the diffusion of industrial robots has been made available by the International Federation of Robotics (IFR) and served as the starting point of many research endeavors. Particularly, the effects of robotization on the labor market outcomes of developed economies have been a hot topic. More recently, there has been a growing body of literature dealing with the question how industrial robots affect world trade and developing countries. For instance, multiple studies have predicted that developing countries are at a greater risk to experience technological unemployment in the near future.

Globalization contributed to growth and prosperity worldwide and provided benefits to both emerging- and advanced economies. To a large extent, developing countries became integrated in the world economy through their involvement in global value chains (GVCs). The establishment of GVCs, in turn, were a direct result of the relocation of production activities from developed- to developing countries. For firms, offshoring is an attractive opportunity as it allows for taking advantage of lower labor costs and greater proximity to growing consumer markets. The strong export position of developing countries are therefore largely based on this labor costs advantage. However, two recent development are challenging this competitive advantage. First, labor cost are observed to be rising in a number of developing countries. Secondly, the possibilities for automation are increasing rapidly and partly eliminate the need for offshoring.

Most of the processes that were previously offshored consisted of routine and labor-intensive tasks. However, this same category of tasks is also most suitable for automation. In the future, further technological development will continuously improve the performance- and lower the cost of industrial robots. Hence, robots are becoming an increasingly attractive investment opportunity for firms. In terms of costs, offshoring and automation are substitutes and thus competitors. Further investment in robotics could therefore lead to a decline in the importance of GVCs and international trade. It is even possible that in the future the world will see a reversal of this process: the reshoring of production activities from developing- to developed economies. In this context, we aim to answer the following research question:

Do industrial robots cause reshoring of production activities away from developing countries?

To investigate this research question we regress some measure of offshoring on the density of industrial robots and other control variables. In doing this, we adopt a similar country-industry level approach as De Backer et al. (2018) and Carbonero et al. (2018). To measure offshoring intensity, an index developed by Feenstra and Hanson (1999), called the offshoring index will be used. This index equals the ratio of non-energy intermediate inputs that are imported from abroad over total non-energy intermediate inputs. Data on the stock of industrial robots is provided by IFR (2018), whereas all other relevant variables are sourced from two datasets by the Organization for Economic Co-operation and Development (OECD). The final panel dataset consist of 29 countries and 15 industries. It concerns an unbalanced panel dataset, spanning the period 1993-2015.

The factors that will be controlled for in the models include: labor intensity, wages, year-dummies, country-trends and industry-trends. The model is estimated using a fixed-effects estimation method. When accounting for trend-variables, our regression estimates provide evidence for a negative and statistically significant relationship between the adoption of industrial robots and offshoring intensity. We estimate that if the density of industrial robots increases by 10% in OECD countries, then offshoring decreases by 0.29%. The results are roughly in agreement with previous literature on this topic. Furthermore, we investigate if the effects are particularly strong for certain industries. However, the estimates for industry-specific regressions turn out mostly statistically insignificant due to small sample size. We instead group industries by their robot-density levels, and find that the effect between robotization and offshoring particularly holds true for industries that have already robotized the most in relative terms.

Several areas for future research exist. Both offshoring and the adoption of industrial robots are concepts that depend on many other factors. However, controlling for all of these is either a too complex- or impossible exercise. Due to the time-constraints of this thesis project, we had to limit the variable selection to those discussed above. Variables that were identified to be important, but are not accounted for are: demand for services, demand for customization features, labor costs in developing countries (e.g. China and India), the costs associated with industrial robots, protectionism and trade barriers. By not controlling for these factors, it is a possibility that our estimators have suffered from omitted variable bias. Hence, an area for future research is to improve the model by controlling for more such contaminating factors. Furthermore, in the literature there exist several contradicting theories on how certain variables are related and what is the best way to model them. Hence, the development of a clear and comprehensive theoretical framework is another contribution that can greatly benefit future research on offshoring.

In most developed countries, support has been growing for policies that specifically deal with the potential disruptive effects of technology on society. One policy that recently came under particular public interest is universal basic income (UBI). UBI proposes that the government redistributes the profits from automation by making a regular and unconditional cash payment to each citizen. However, these policies do not cover citizens of developing countries, which multiple studies predict have a greater risk of becoming technologically unemployed. Most of these countries do also not themselves have the jurisdiction or funds available for enacting policies like UBI. We therefore propose that, since the developed world and particularly MNEs are partly to blame for the disruptive effects to developing countries, global collective action is needed. There exist several possibilities for doing this, for instance by introducing a type of UBI policy that covers the entire world. However, it is difficult to see how such a policy could be implemented on a global scale because of the many different actors that need to be involved, and even if it is possible, it will likely take a considerable amount of time to establish. In the short-term, therefore, a better solution might be to provide extra international aid or to work together with governments of the developing world in order to improve eduction systems, labor unions and social security.

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Ralf Bendermacher
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1. Introduction

Both trade and technology have long been important topics in economic theory. However, within economic debate, discussions primarily focused on how trade and technology affect economic outcomes. The relationship between these variables themselves has received much less attention. The perception that technology and trade are mutually reinforcing is still very prevalent today. This has been true and quite evident for technological developments belonging to the past. For instance, advances in aviation and telecommunications have significantly lowered transportation and communication cost, and partly explains why the world has experienced such a rapid growth in international trade during the past decades.

The increase in world trade primarily materialized through an upward trend in offshoring and the establishment of global value chains (GVCs). Previously, the main motivating factor for firms to relocate production activities towards emerging markets were lower labor costs. For developing countries, this extra economic activity provided a chance to integrate more fully into the world economy. However, to this day, the development and industrialization of these countries strongly depend on this competitive advantage in labor cost.

However, current developments are changing the cost-benefit analysis for firms, with respect to the location of production, once again. First, in many developing countries labor cost have started to increase during the last decade. For workers, higher wages is obviously a good thing. However, if this causes firms to decide against offshore outsourcing or foreign direct investment, there would be less opportunity for work and employment would decrease. Furthermore, workers in developing countries are increasingly facing competition from industrial robots. The range of tasks that robots can perform, is continuously increasing. As is usually the case with technology, prices fall while performance improves. This explains why firms have increasingly started to adopt industrial robots into their production activities. Over the past years, there have been many cases of "botsourcing": firms building new factories consisting of highly automated production processes. One example of this phenomenon is Adidas that recently opened completely automated "Speedfactories" in Germany and the United States. Here, industrial robots are used to produce custom sneakers or quickly replenish models that are sold out. Another example is Tesla's "Gigafactory" that is currently under construction in the United States. Also here, machines will do the vast majority of the work and the job of most employees is simply to oversee the robot workforce.

For the most part, industrial robots affect routine and labor-intensive tasks, which is also what characterizes work in developing countries. Hence, in terms of production cost, robots are competitors to foreign employment and thus diminish the labor cost advantage of developing countries. Indeed what the above examples seem to show is that, botsourcing often goes hand in hand with local production. This could thus lead to less offshoring in the future or even the reverse process to happen: reshoring (i.e. moving previously offshored activities back into the home country). A direct example of reshoring is given by Apple, that has shifted some of its activities in China, primarily through its business with the Taiwanese contract manufacturing company Foxconn, back to the United States (Marin, 2018). While the need for firms to relocate production processes to foreign markets is eroding, the importance of GVCs is decreasing. This could possibly offer an explanation for the slowdown of world trade that has been documented by Timmer et al. (2016) in recent years. Some economists, therefore, claim that reshoring is becoming a new trend in the 21st century. This is bad news for developing countries, as this has the potential to hinder their economic development and structural transformation. Offshoring and the emergence of global value chains were a major contributor to productivity and employment growth, rising living standards and declining poverty rates.

There are also concerns for developed countries, because also here automation is expected to disrupt labor markets by declining real wages, rising unemployment and greater income inequality. However, the adoption of industrial robots has the potential to increase productivity and output, which could set a manufacturing renaissance into motion. Unsurprisingly, these developments are met with both high expectations and deep concerns.

1.1 Research question and sub-questions

In the light of the above, this thesis aims to quantify how much the adoption of industrial robots in developed countries contributed to the decline in world trade experienced in recent years. Specifically, it poses to answer the following research question:

- Do industrial robots cause re-shoring of production activities away from developing countries?

To effectively answer this question, it will be divided into the following sub-questions.

- What forces have driven offshoring in the past?
- What forces are driving offshoring in the present?
- What are the main factors that affect the adoption of industrial robots?
- Is an increase in robot density at the industry level associated with a reversal or slowdown in offshoring?
- Is this effect especially striking for particular industries?
- What kind of policies can help developing countries to tackle possible disruptive effects?

1.2 Thesis outline

The first three sub-questions will be answered by conducting a literature review combined with studying actual data on offshoring and the adoption of industrial robots. For this purpose, a broad literature review is presented in chapter 2. Research on the effects of industrial robots on offshoring and developing countries is still in its infant stages. Previous studies on the effects of industrial robots focused predominantly on labor markets of developed economies. In this field, a vast amount of literature is available and clear theoretical frameworks, such as the one presented by Acemoglu and Restrepo (2015), have been developed. In the case of offshoring, however, such frameworks and sources for theory building are mostly lacking. As we included some of the theories concerning technology's effect on the labor markets and economies of developed countries in the literature review, it might at times seem unrelated to the research topic. However, the theories on both topics are often intertwined, so including them can provide useful insights.

The fourth and fifth sub-questions will be answered by a regression analysis. In this study we will adopt an industry-level approach and use data on the industrial use of robots, made available by the International Federation of Robotics (IFR). A second objective of this thesis is to provide a robustness check of the studies De Backer et al. (2018) and Carbonero et al. (2018). We will therefore follow a similar approach and base certain decisions we make, such as including control variables, on these studies. Replicability is one of the hallmarks of scientific study and the value of replicating the results of previous studies is that more confidence can be placed in these results. Chapter 3 further elaborates on the research methodology and presents the model we use to estimate the results. The data sources, and how these are used in the construction of the relevant variables, are discussed in chapter 4. Chapter 5, presents the descriptive statistics of the important variables that are included in the estimation model. Chapter 6 present the results of the analysis.

Chapter 8 draws the conclusion and highlights possible areas for future research. Finally, chapter 9 concludes this thesis by discussing how the actual effects of automation can turn out different to what we predicted. This chapter furthermore discusses what the responsibility of developed countries is in causing technology-induced disruption in the developing world, and how existing policy proposals that deal with automation can possibly be used to tackle such issues.

2. Literature review

2.1 Background

Since the industrial revolution, technological development has dramatically changed our perception of the world and the way we live our lives. Generally, most people perceive the introduction of new technologies as something society “benefits” from. For instance, nowadays we enjoy the possibilities to communicate with almost anybody in the world and to instantly access whatever kind of information we are looking for. However, it does not always have to be the case that new technologies are beneficial to society. Talking about the effects of new technologies remains somewhat fuzzy as different technologies affect different people and often in different ways. Technologies should therefore always be approached from a specific context. Most studies on the effects of new technologies usually focus on two areas:

- Social: how do new technologies change the way we think about and interact with the world around us?
- Economical: how do new technologies impact economies and the organization of work?

The effects of technology on economies and the labor market has been of concern to economists for a long time. People that enrolled in an introductory micro-economics course should have some familiarity with a concept named technological change or progress and why it is important for economic growth. Technological change refers to the use of new or improved methods in the production of goods and services, which allows the same output to be produced with less inputs. Technological change is the result of inventions and innovations and can take on many different forms. Depending on how the capital labor ratio changes, technological change can be either neutral, labor-saving or capital-saving. Historically, economists have often tried to determine the direction of technological change. On many occurrences it was hypothesized that technological change was inherently labor-saving from which thus follows that industrial and technological advances cause unemployment. Until now, however, previous claims that technology would cause unemployment turned out to be false over and over again. For instance, in 1980 the economist Jeremy Rifkin predicted the “End of Work” to be near. A couple years later, however, US unemployment was at an all-time low during the dot.com bubble. In the past, technological change did cause some jobs to become redundant in certain industries. Therefore, in the short run, some unemployment arose as a result of this. However, in the long run economies adjusted to the new technologies and new jobs were created. After these shifts have played out, the economy will again be in full employment in equilibrium. Examples of this are the automobile and the computer. Computers did cause some jobs to become redundant but overall complemented human intelligence and even created entire new sectors (Brynjolfsson and McAfee, 2014).

New technological developments together with the fact that many advanced economies are experiencing a high rate of joblessness, slow growth of real wages and continued inequality have again sparked concerns that technology is eradicating jobs and causing unemployment (Freeman, 2015). Optimists label the new concerns as “technocratic” or “science-fiction” thinking and state that the market will again take care of itself by the forces of demand and supply will ensure full employment in equilibrium. Others, however, are more pessimistic and warn that the world is starting to experience a new technological revolution that will have an entirely different impact on society than those of the past.

In recent times, one area of technological change that is under particular scrutiny is automation. In simple terms automation can be defined as the utilization of technology in production processes, in such a way that only minimal human assistance is necessary. Historically, primarily routine and lower-skill tasks were at risk of being automated. During the industrial revolution, for instance, mechanization primarily affected repetitive and physically demanding work. A large number of economic thinkers therefore theorized that technological change is skill-biased. Skill-Biased Technical Change (SBTC) is defined as a shift in the production function in favor of skilled labor (e.g. more educated or experienced) instead of unskilled labor (Violante, 2008). If true, those who hold jobs at the higher skill-levels do not need to fear technological change. The assumption being made is that technology and skills are complementary: skilled workers are more likely to possess the necessary skills for, or learn the additional knowledge needed for, working with new technology and will therefore reap more of its benefits. This will increase the relative productivity and demand of skilled labor. A study by Autor, Levy and Murnane (2003) indeed showed that, based on occupational data, the relative industry demand for non-routine tasks increased sharply relative to routine tasks since the 1970s.

Today, the world is facing the emergence of a new wave of automation technologies, that include: 3D printing, self-driving cars, virtual assistants and industrial robots. A famous study conducted by Frey and Osborne (2013) states that 47% of jobs in the United States are at high risk of being automated. This was a shocking revelation to many economists and policy-makers as it suggested that even service jobs and tasks depending on cognitive skills were no longer immune to technological change. Other studies confirmed these results and it is predicted that in the future artificial intelligence is likely to outcompete human intelligence in many areas (Freeman, 2015). One example is that of intelligent pattern recognition software that in the future will have the potential to replace lawyers and doctors (Brynjolfsson and McAfee, 2014). As it becomes possible for machines to outperform workers in an ever increasing amount of tasks, both skilled and unskilled workers will be at risk of substitution. The emergence of these new wave of technologies has therefore again raised concerns of possible negative technology effects, which blew new life into the still ongoing discussions on technological change.

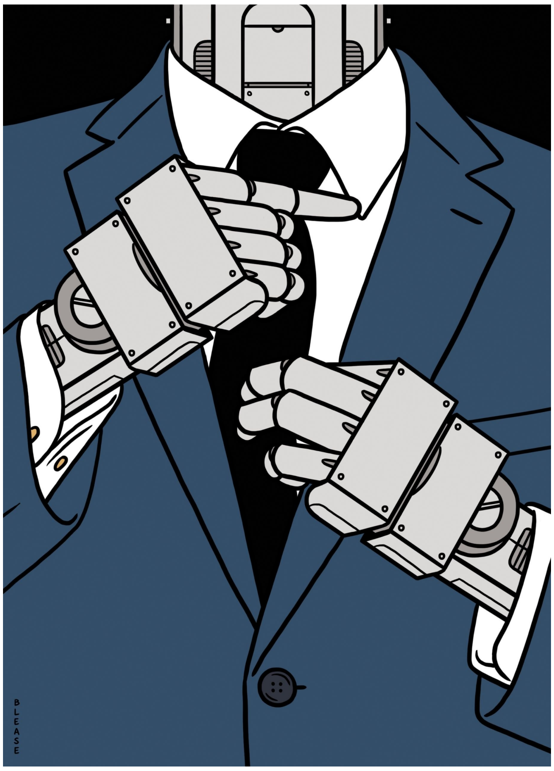

Figure 2.1: Are robots skill-biased?

2.2 Economic developments and new areas of concern

The new concerns on technology are not just based on studies predicting a high percentage of jobs becoming redundant in the future due to automation. Over the past decades, some economic developments have been observed in the data and could potentially have serious consequences for the future. As some of these developments could partially be explained by technological change, this supports the wariness of new technologies. In what follows we will give a short discussion on three of these developments.

2.2.1 Decline of the labor share

Income (GDP) is distributed between the two factors of production, labor and capital (i.e. the functional distribution of income). Labor's share of income is the compensation of employees and is paid out in the forms of salaries and wages. Capital's share of income is usually paid out in the forms of interest or dividends and is distributed only between the owners of capital (e.g. private or stock). In the article "The global decline of the labor share", Karabarbounis and Neiman (2013) document that since the early 1980s, labor's share of income has significantly declined globally. The decline was observed within the large majority of countries and industries: out of the 59 countries and 10 major industries included in the analysis, 37 countries and 6 industries experienced a significant decline in labor's share, respectively. Since the early 1990s this trend is also observed in most developing economies (Dao et al., 2017). Figure 2.2 depicts the decline in the labor share for Germany, the United States and Japan.

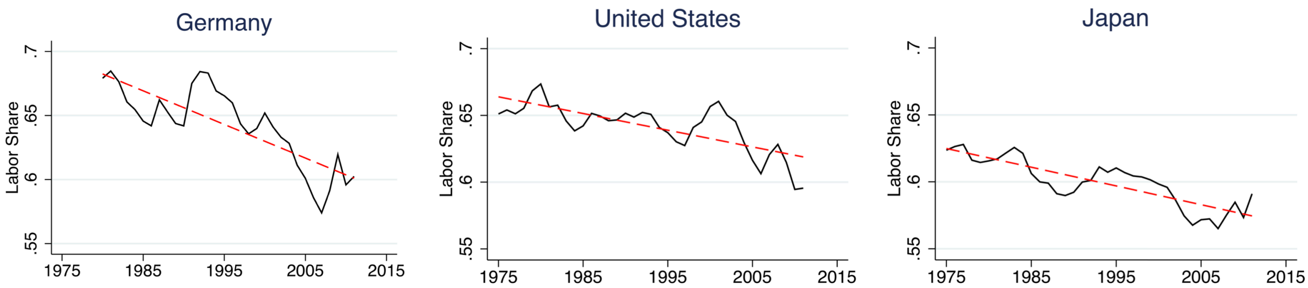

Figure 2.2: The decline of the labor share (Karabarbounis and Neiman, 2013).

Labor's share of income can be written in formula as: (wL)/(PY) = (w/P)/(Y/L), where w/P is the real wage and Y/L is labor productivity. Hence, a falling labor share implies labor productivity grows faster than real wages (Dao et al., 2017). If labor's share of income exhibits a downward trend, this naturally means that the share of income going to the owners of capital is on the rise. In most countries, the owners of capital represent only a small fraction of the total population. For this reason, capital's share of income is more unequally distributed than labor's share of income. A reduction of labor's share of income would therefore increase total income inequality (Bogliacino et al., 2016). Piketty et al. (2003) empirically showed that over time and across countries, a higher capital's share of income is indeed correlated with greater income inequality.

Karabarbounis and Neiman (2013) attributed this trend to a decline in the relative price of investment goods (e.g. lower costs of information technology) and thus the cost of capital. This has induced firms to shift away from labor toward capital. According to their study, roughly half of the decline in the global labor share can be explained by a decline in the relative price of investment goods.

However, there exists considerable disagreement with this explanation. Although, the decline in labor's share is observed in most developing countries, there exists a lot of variation between them. Since the adoption of technology is fairly homogenous within the developed world, it is therefore unlikely that technology is the major factor causing shifts in the distribution of income. Naudé (2019) also states that current and past changes in inequality should not be straightforwardly ascribed to technological change and identifies globalization and the erosion of labor market institutions to be more important determinants of the rising inequality since the 1980s. Globalization and trade have increased competition between firms and made it easier to relocate production tasks abroad over the past decades. At the same time, the power of labor unions have weakened throughout the developed world and considerably lowered the bargaining power of labor. This can also explain why income inequality is higher in the US than in Europe, since US labor market institutions are weaker.

Another explanation is given by Autor et al. (2017), who explains the decline in labor's share of income by the idea that especially the most productive firms have advantaged from globalization and technology. This causes industries to become characterized as winner-take-all markets and dominated by a small number of "superstar" firms that gain the majority of the market. Studies show that these same firms are also often characterized by high profit-margins and low labor-shares (Autor et al., 2017). Therefore, as the influence of these superstar firms increase, the aggregate labor share will tend to fall. For instance, the coming of the internet has allowed firms to adopt different business models such as the "platform" model. Ever since the digital economy became a thing, digital markets have tended to favor large platforms that hold the majority of a market. Examples of such platforms are Facebook, Twitter and Amazon. Multiple explanations exist for why winner-take-all markets have become so common. First, digital goods and services are very easy to reproduce and distribute. Second, global economic integration has increased the potential customer-base for firms. Third, consumers have become more quality- and price-sensitive. And finally, these newer business models often rely on network effects to grow. The greater the customer-base of a platform, the greater its value becomes and the more new customers it will attract. These network effects raise the switching-costs for customers and the barriers-to-entry for competitors (Furman and Seamans, 2018).

Furthermore, the reduction of labor's share in income is also observed in developing economies. However, the evidence in the case of developing countries is somewhat more ambiguous as it shows greater fluctuations and oscillations. The results of most developed countries, however, are in agreement and exhibit a secular downward trend in labor's share of income.

2.2.2 Decline of world trade

Historically, there have been periods of contracting and expanding levels of world trade. The literature identifies the primary factors that influence these "waves" of globalization to be: technological change, the establishment of international organizations, industrialization of developing countries, political movements, trade liberalization reforms and periods of war (Robertson, 2003).

Since the 1960s, international trade has increased considerably and most often grew faster than global production itself. In 1960, the trade share, the sum of imports and exports as a share of gross domestic product, was 12.5 percent for an average OECD country. In 1990, this had increased to 18.6 percent (Krugman, 1995). This increase is most often attributed to the technological breakthroughs and inventions of recent history. Railroads and the jet engine have continuously lowered transportation costs and were a prerequisite for the high levels of world trade we know today. More recent developments like the microprocessor and the internet, made high-speed communication and digital trading possible from almost any two places in the world. It is not surprising therefore that technological change and world trade have been theorized to be mutually reinforcing.

One explanation for the dramatic increase in world trade is the international fragmentation of production. From the perspective of economies of scale, it is inefficient to perform many different tasks and operations in the same production facility. From this stems the idea of

global value chains (GVCs): slicing up the value chain in a number of stages, where each stage is done at a specialized plant in a certain location holding some comparative advantage. When each component of a final good originates from different locations, world trade expands and it even becomes possible that the sum of imports and exports in the production of a good exceeds its value added (Krugman, 1995).
However, since 2011 economists have observed a slowdown of world trade (Timmer et al., 2016). Figure 2.3, graphically displays the annual growth rate of world trade since the start of the third millennium. From this can be observed that during the global financial crisis, world trade fell sharply into the negative. Although it quickly recovered from this, its rate of growth has been either on decline or level since 2011.

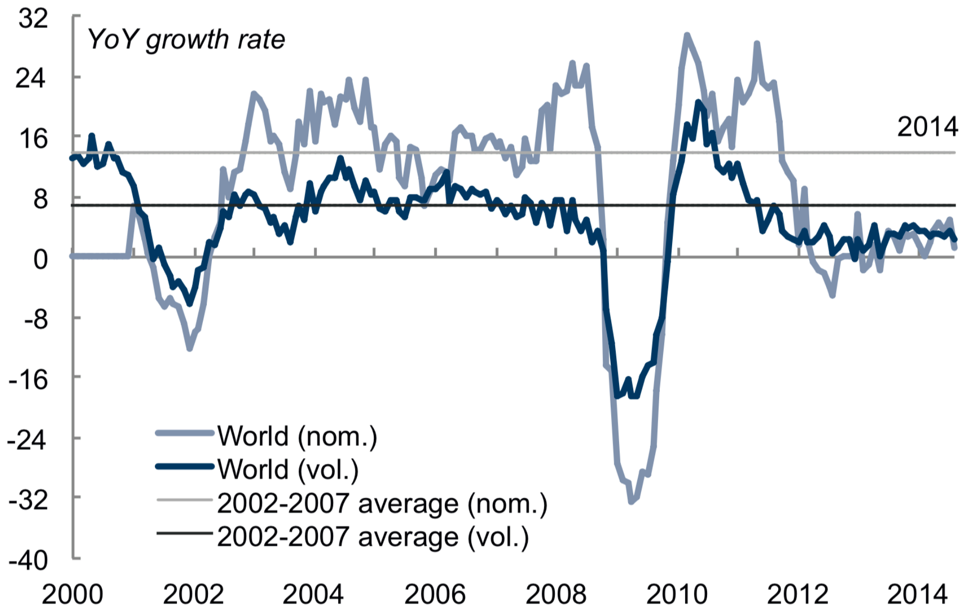

Figure 2.3: World Trade (Boz et al., 2015).

Two possible explanations for the slowdown of world trade growth have been offered in the literature:

- The international production fragmentation has stalled. Instead of long and complex global value chains (GVCs), firms have started to favor local production and decide against moving parts of their production processes abroad. Reasons for this decline in the importance of GVC's are: (1) increased trade costs due to protectionism, (2) increasing production capabilities of developing countries, such as China, that subsequently require fewer imports as more of the products are produced domestically, and (3) technological innovations that increase the possibilities for automation. When production becomes more localized, less intermediate inputs are imported and as a result world trade declines.
- The composition of final demand changed in favor of services, which are much less trade intensive. In recent years, services account for a larger share in final output compared to goods. Since the production of services uses on average less imports than the production of durable goods, the global import intensity declines. Although trade in services has grown in recent history, most services are still non-tradable (De Backer et al., 2018).

2.2.3 Premature deindustrialization

The industrial revolution enabled sustained productivity growth in Europe and the United States for the first time. This caused the world economy to become divided in poor and rich countries (i.e. developed and developing countries). Again, it was industrialization that allowed some countries, such as Japan, Korea and Taiwan to successfully catch up. Industrialization has affected the modern world in ways beyond economical: urbanization, mass franchise, social classes and habits that we are accustomed with today are in effect all a product of industrialization. However, many of today's advanced economies have already moved into a new, post-industrial development phase.
Industrialization can be measured using manufacturing's share in total employment and manufacturing's share in value added (at either constant or current prices). Economists have observed a pattern in the way countries industrialize. The initial industrialization phase increases both manufacturing's shares and income. However, at some point there is a turning point and both manufacturing shares start to decline when income increases. Not surprisingly, this phenomenon is called deindustrialization in the literature (Rodrik, 2015).

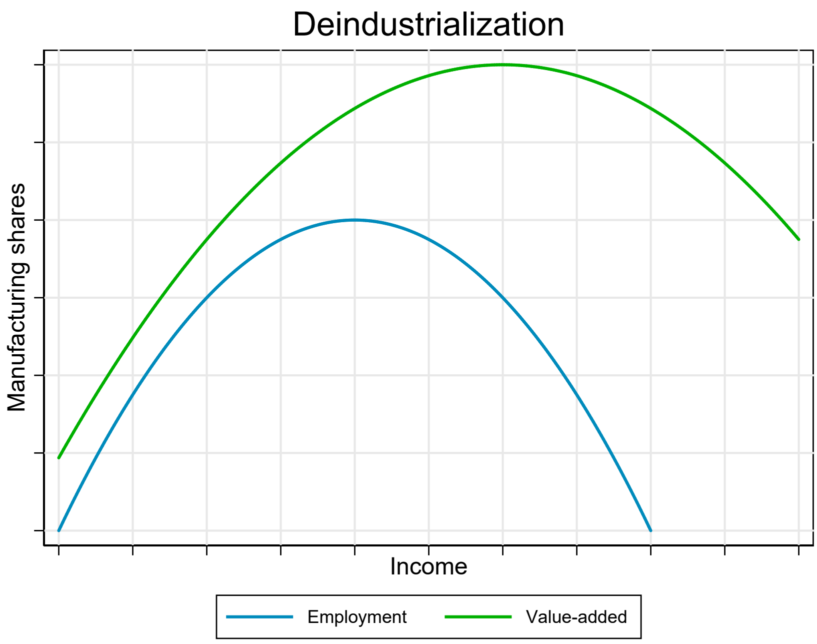

Figure 2.4: Industrialization and deindustrialization

When plotted against per capita income, both shares of manufacturing first rise and subsequently tend to fall over the course of development, see figure 2.4.
Rodrik (2015) provides two reasons why the manufacturing shares eventually tend to fall:
- Demand-based: consumption preferences shift away from goods towards services. This would have a similar negative effect on both the employment and output shares of manufacturing.
- Technology-based: new technologies cause rapid productivity growth in the manufacturing sectors of the economy. This, however, only affects the employment share of manufacturing.

The fact that these two forces affect the two measures differently, helps explain why they have different turning points. The employment share tends to have a turning point early in the development process compared to value-added, see figure 2.4.

Deindustrialization is a common fate of industrializing countries and has become more rapid over time (Rodrik, 2015). Furthermore, it was found that the pattern of deindustrialization is even more striking for developing countries. For these countries, manufacturing shares have started to shrink much earlier compared to the levels at which advanced economies started to show deindustrialization symptoms. Most of the manufacturing industries in developing countries were a product of the increasing world trade and the establishment of GVCs and thus fairly young in temporal terms. Hence, when symptoms of deindustrialization start to show, without the country ever going through a proper industrialization phase, the phenomenon is also called: premature deindustrialization. Moreover, these lower peak levels are reached at lower levels of income. Premature deindustrialization is of big concern as it can have serious economic and political consequences, including: inequality, loss of jobs and decline in innovation capacity (Rodrik, 2015).

2.3 Industrial robots

The OECD has identified three major technological developments that will reshape the organization of production to be (De Backer et al., 2018):

- Internet of Things (IoT): a system of interrelated physical and information-sensing devices. These devices will interact and communicate with each other by transferring data over the internet without the need of human interaction.
- Big data: data-processing software that can analyze large sets of data to reveal patterns, trends and associations.
- Cloud computing: data centers consisting of large amounts of storage and computing power that are made available to multiple users on demand over the internet.

A large number of applications and technologies have originated out of the conjunction of these developments. One of those is a type of automation technology that some people expect to bring about a new industrial revolution: industrial robots. The International Organization of Standardization (ISO) defines an industrial robot as follows: “an automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications” (ISO 8373:2012). Industrial robotics currently receives a lot of attention from the academic world as it is considered to be the ‘leading edge’ automation technology at present (Naudé, 2019). Furthermore, data on robot adoption by country, industry and year have been made available by the International Federation of Robotics (IFR), encouraging further research on the topic.

Industrial robots have existed for quite some time already. In the past, industrial robots were primarily adopted by the automotive and other manufacturing industries. The reason these industries were so early in adopting robots into their production lines is because they are characterized by repetitive, heavy and dangerous tasks together with a high degree of labor intensity (De Backer et al., 2018). In other industries, most tasks remained confined to human labor as they needed cognitive or fine motor skills to be performed.

Figure 2.5: Industrial robots in the automotive sector

Recent data by the IFR shows that many industries have increasingly started to adopt robots in their production lines for a wider variety of tasks (IFR, 2018). Two reasons for the increasing rate of robot adoption among industries can be identified:

- Robots are becoming more capable, efficient and economical. Over the past few decades, technological developments have profoundly improved the capabilities of robots, allowing them to perform an increasing amount of tasks. Robots are becoming increasingly more autonomous, flexible and versatile and can be employed to perform a growing number of tasks. In comparison to human labor, robots can work around the clock, deliver continuous output and greater contributions in terms of productivity. Industrial robots also have the potential to improve the reliability and quality of production processes and can be used to work in hazardous environments (Kinkel et al., 2015). Moreover, the installation and operating costs of industrial robots has fallen sharply in the past decade (Carbonero et al., 2018). As industrial robots are even becoming a viable production method for smaller businesses, it is expected that this robotization trend will continue to pick up pace in the future (De Backer et al., 2018).
- Product life cycles have become shorter and people increasingly value products with customization features. To maintain a competitive advantage, firms need to continuously innovate, offer products in greater variety and in smaller quantities. When production is organized in long and complex GVCs, responding to market signals is a lengthy process. Besides that, GVCs expose companies to large levels of supply chain risk in the event of adverse shocks to the economy. At the moment, stationary and task-specific machines are making room for mobile, flexible and re-programmable robots that enhance the flexibility of the production process. It will therefore become easier for firms to make adjustments to a production line or to restructure an entire manufacturing floor, allowing them to meet customer demands more precisely and bring products to market faster. Industries where market demand and consumer preferences change quickly can especially benefit from industrial robots (De Backer et al., 2016).

The adoption of industrial robots first took off in OECD economies as it helped to compensate for high and rising labor costs and safeguard international competitiveness (De Backer et al., 2018). In recent years, investment in industrial robots is also observed in emerging economies. These investments are often supported by the respective governments as part of their industrialization and development strategies (De Backer et al., 2016).

2.4 Technological change and industrial robots

Thus far we have often talked about technological change in general. The literature on the economics of technology already goes far back in time. Technological change is a somewhat abstract concept and is not easily measured by itself. However, several proxies exist for this purpose. In the academic literature one often encounters R&D expenditure, patent count, ICT investment or total factor productivity (TFP) growth as measures of technological progress.

However, as previously discussed, technological change that is happening today is different both in kind and in effect to those of the past. From this moment on, therefore, we focus our attention not on technological change per se, but rather on the automation and robotization revolution that is taking place at this moment. Robotization can be measured directly by the actual stock of industrial robots, which is a measure that has been in wide academic use during the last couple year. This data has made available by the IFR for a large group of countries, The IFR dataset concerns annual data on both the stock and flow of industrial robots, classified by industry (De Backer et al., 2018; Acemoglu and Restrepo, 2017; Kromann et al., 2015).

2.5 Industrial robots and labor markets
Historically, research on technological change has particularly focused on how it affected labor markets of industrialized economies, in terms of employment, wages, productivity and income disparity. This is also the case concerning the literature on industrial robots. We will start by discussing some of the most important research areas and results regarding industrial robots and labor markets.

2.5.1 Productivity
Concerning the effects of industrial robots on productivity, the literature is overall in agreement. Kinkel et al. (2015) suggest that the introduction of robots into industrial processes can, by optimizing economies of scale, improve the overall productivity of those processes. Through substitution of human activities, industrial robots improve total factor productivity together with the reliability and quality of the production processes. Zanker and Jager (2015) provide evidence based on firm-level data that companies using industrial robots in their production processes obtain greater productivity than those who do not. Kromann et al. (2015), looking at industry-level data, found that in both the short-term and in the long-term, automation has a significant impact on labor productivity. To quantify the possibilities in terms of productivity gains, they estimated that in the case of the UK, if each industry were to increase its robot-density to the highest level among countries, productivity would increase by 22% and 7% in the short- and long-term, respectively. However, they state that because the level of specialization within each industry differs in each country, it might not always be feasible to automate to such an equal extent.
It is believed that technological developments, such as industrial robots and AI, enable even more follow-up innovation to happen. Since innovation is also by itself linked to economic growth in the literature, the effects on productivity could be even greater (Furman and Seamans, 2018).
Economists are generally enthusiastic about the prospects of technology on economic growth. According to Miller and Atkinson (2013) automation and robotics are the core drivers of the technology-driven changes that are taking place and that will increase productivity. Since greater investment in industrial robots has the potential to increase productivity, it could in theory improve the welfare of all people. From this point of view and the fact that many people are unwilling to perceive threats, it is hard to make a case against further robotization. However, when considering the expected impacts of automation on other labor market outcomes, future prospects are less optimistic.

2.5.2 Wages, the skill premium and income inequality
Most firms produce output using the most cost-effective method. Therefore, whenever it becomes cheaper to perform a task using robots, then unless workers take pay cuts, this task will eventually be assigned to robots. Increased substitutability by robots this puts downward pressure on wages. As technological development is likely to further improve the competence and lower the cost of robots, this trend in wages is likely to grow in the future (Freeman, 2015). Research findings suggest that while labor productivity has increased over the years, slow growing real wages cause labor's share of income to decline.

Technology might impact the distribution of income in two ways:
- Between labor's and capital's share of income: If greater use of automation means that overall less labor is used in the production of goods and services, then labor's share of income declines. Capital ownership is concentrated at the top of the income distribution. Hence, when the owners of capital obtain a larger share of income, inequality increases (Marin, 2018).
- Within labor's share: Automation might also affect the distribution of wages within the workforce (i.e. between different types of workers), something which is often called the wage gap. There are two opposite hypotheses on how technology affects the wage gap, depending on whether technology and labor are seen as complements or substitutes. If technology and skills are complements then as technology progresses, the demand for skills to work with technology increases. Only those educated on the technologies can profit from this and the skill premium increases. As an example: during the early 1990s,

people that possessed the necessary skillset to operate a computer were obviously enjoying an advantage over those who did not. As the demand for skills rise, the wage gap between skilled and unskilled labor (i.e. the skill premium) rises accordingly. Technological change that is assumed to be skill-biased (SBTC) would therefore imply a greater skill premium. However, if technology and skills are substitutes then as the capabilities of machines increase, more and more workers become redundant. As eventually even skilled workers, such as lawyers and doctors are replaced by intelligent machines and if no new skilled-jobs are created, the wage gap narrows in response to technological change (Marin, 2018). In theory, technologies can at the same time substitute and complement different type of workers. From a historical standpoint, cases can be identified where technology has either narrowed or widened the wage gap. For instance, during the first Industrial Revolution, innovations primarily complemented low-skill workers and substituted for skilled artisans. As the demand for low-skill labor rose, wage inequality declined (Naudé, 2019). However, during the ICT-revolution, technology primarily complemented higher-skilled workers and as their demand increased, the wage gap widened. Regarding the effect of more recent technological change on the wage gap, the academic literature is not always in agreement. Graetz and Michaels (2015), provides evidence for the first hypothesis as they showed that from 1993 and 2007, robots have especially reduced the employment share of lower-skilled workers, while no significant effect was found for higher-skilled workers. Goldin and Katz (2009) document that since 1980s, the wage gap in the United States by education, occupation and age all widened substantially. However, Marin (2018) observes that in most Western countries, except the United States and Germany, the skill premium is declining while unemployment is rising among skilled workers. As discussed above, one possible explanation for this is technological change, causing the demand for skills to decline resulting in a narrowing of the wage gap. However, many other factors could have attributed to this, such as: improvement of educational systems, change in the minimum wage and labor unions.

There is an ongoing discussion among economists whether income inequality is actually something undesirable or not, as it can theoretically both benefit and harm an economy. Some economists defend the “top one percent” and argue that their efforts contributed to economic growth and therefore benefited society at large. Some inequality is necessary to act as an incentive for people to work harder. From this perspective, inequality is a price we need to pay for technological progress and economic development. If the profits from innovation are taxed more and the distribution of income narrows, the incentive for entrepreneurship is lowered. However, numerous international organizations have raised concerns that too much inequality in the distribution of income would endanger social cohesion. For instance the OECD, an organization that has long advocated for economic growth and often supported labor market reforms that increased inequality, now worries that inequality could hamper future economic prosperity (Freeman, 2015). Recent research suggests that social tension, and thus inequality, can indeed harm economic growth (Dao et al., 2017).

2.5.3 Employment

In economics, a change in the price of one factor of production shifts the iso-cost curves. Generally, this affects both the demand for labor and for capital. The effect of such a price-change on demand can be decomposed in two components: the substitution effect and the income effect. For instance, a reduction in the price of capital induces two opposite effects on the demand for labor. As capital becomes relatively cheaper, firms substitute labor for capital and the demand for labor declines. However, a fall in the price of capital and thus total production cost, enables firms to increase output. When output rises, labor-demand will too. The effects of robotization are not simply caused by falling prices since also the capabilities have increased over the years. Industrial robots and technological innovations in general act in a somewhat more complex way as they also affect the shape of the production isoquants. However, in some sense the theorized effects of industrial robots are similar to a fall in the price of capital. Acemoglu and Restrepo (2017) list the two opposite employment-effects of industrial robots as follows:

- *Displacement effect (-)*: If industrial robots and workers compete in the production of different tasks, then they will directly displace workers from performing specific tasks where labor is more costly or less efficient.
- *Productivity effect (+)*: Robotization allows tasks to be performed at lower costs and more efficiently. This reduces the marginal cost of production and gives rise to an increase in productivity and output. As the sector that adopted the robots expands, employment increases within the industry. Furthermore, when output in one sector increases this can spillover into other sectors of the economy, increasing overall employment. Higher incomes lead to greater investment and consumption, which increases demand for jobs throughout the economy. For example, if income increases households spend more on leisure and hospitality, thus creating jobs. Furthermore, technology has the potential to change business models and therefore create entire new sectors. An example of this is the internet: as e-commerce became a possibility, jobs were lost at department stores but new opportunities were created at fulfillment and call centers (Furman & Seamans, 2018). Hence, through greater efficiency and productivity increases, robotization expands labor demand both within the robot-adopting industry and indirectly in the overall economy, through the output increases of the former.

When a technological innovation is adopted by an industry, both effects likely occur concurrently. Technological change affects labor markets not only through the industries that are directly impacted by the new technologies (i.e. those who install robots) but also through adjustments in other parts of the economy (Chiaccio, 2018). The overall labor market will experience a net effect that has a sign dependent on which of these effects is stronger.

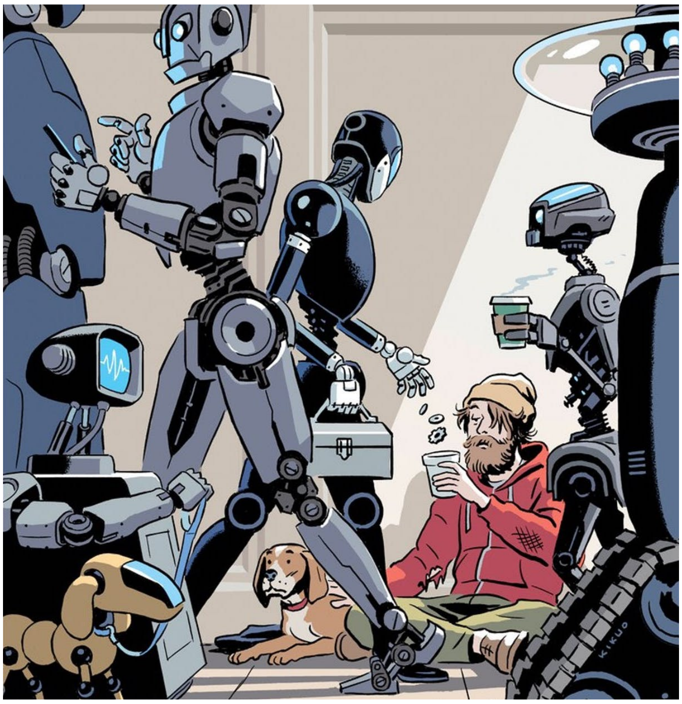

Figure 2.6: Technological unemployment

One way to study the effects of technological change on labor markets is to look at the past. Historical cases, like those during the industrial revolution, suggest that the displacement effect most often dominates in the short run but over the long run, markets and society become adapted to the technological developments, and through the expansion of industries or the creation of new jobs, the productivity effect gains in force and leaves behind a positive impact on employment (Chiacchio, 2018). For instance, Bessen (2017) found that computer technology was associated with job growth particularly in non-manufacturing and service sectors. In these cases the productivity effect overruled the displacement effect. However, just because the productivity effect was greater than the displacement effect for the technological changes of the past, inductive reasoning that it will hold again for future technological generations would be a false argument.

Currently there exists a large body of literature looking at the effects of the increased adoption of industrial robots on employment. The following section discusses the methods and results of the most notable research papers identified in the literature:

- One of the most cited and first studies to use IFR data, Graetz and Michaels (2015), look at the effects of robotization on employment, productivity and economic growth. Using a sample of 17 countries they conclude that the increased use of robots per hour worked from 1993 to 2007 raised the annual growth of labor productivity by 0.36 percentage points. A statistically significant relationship between robot adoption and unemployment is not found for developed countries. Besides contributing to annual labor productivity growth, the study concludes that increased robot adoption raises total factor productivity, boosts average wages and lowers output prices. Although, unlike other studies, a positive and significant relationship is found between robot adoption and hourly wages, they conclude that these gains are not shared equally across workers. When looking at different skill groups, they found that for higher-skill workers the relationship between robots and wages was indeed positive, but insignificant. The coefficient estimates for low-skilled workers, however, are large, negative and statistically significant.
- Acemoglu and Restrepo (2017) develop a local labor market equilibrium approach to study which of the two labor market effects (displacement effect and efficiency effect) dominates in the case of industrial robots. They find that one extra robot per thousand workers negatively effects the US employment to population ratio and wages by 0.2 and 0.37 percentage points, respectively. They construct a variable known as exposure to robots that is equal to the number of industrial robots per thousand workers and, accounting for control variables, regress this on wages and employment. The idea supporting this approach is that the higher someone is exposed to robots in the work environment (i.e. the higher the robot density of the employing sector) the more the employee is at risk of experiencing lower wage growth or losing employment altogether. Furthermore, they look at how robot exposure effects different sub-groups (working classes) of the population.
- Chiacchio, Petropoulos and Pichler (2018), apply the same framework developed by Acemoglu and Restrepo (2017) in the context of European labor markets. In total, they examine the influence of industrial robots on wages and employment in six European countries that together make up 85.5% of industrial robots on the EU market. These include: Finland, France, Germany, Italy, Spain and Sweden. It was found that one extra robot per thousand workers reduces the employment rate by 0.16-0.20 percentage points. Hence, just as in the study by Acemoglu and Restrepo (2017), the displacement effect appears to dominate in the case of industrial robots.
- Frey and Osborne (2017) conducted a forward-looking study on the susceptibility of jobs to automation and computerization. What this means is that, based on current and predicted technological developments, they estimated the feasibility or likelihood that automation technologies could substitute workers in specific occupations or tasks in the near future. They concluded that 47% of all jobs in the United States will be threatened by automation within one or two decades. A similar study based on the European labor market was conducted by Bowles (2014), who estimated that 54% of EU jobs were at risk. However, the methodology of these studies has received some criticism for not looking at specific tasks. It is therefore possible that the risks were overestimated.

2.6 Industrial robots and developing countries

Besides its impact on labor markets of advanced economies and within-country inequality, a more recent topic of interest concerning automation is how it affects emerging economies through world trade and globalization, and thus global inequality. Optimists would say that new technologies, such as industrial robots, represent an unprecedented chance for these economies to develop into a more advanced one. Pessimists, however, worry that since richer countries have much greater capacity to capitalize on new technologies, developing countries will become even less capable to compete in the world economy (Rodrik, 2018). Although the adoption of industrial robots has also started in developing countries, so far it has been mostly confined to the developed world. However, this does not mean that developing countries remain insulated from the impacts of industrial robots.

As explained before the global economy has over time become increasingly integrated. Previous technological developments made offshoring, relocating parts of the production chain abroad, an easier and less costly undertaking for firms. Offshoring allows for taking advantage of: lower labor costs, access to critical resources and proximity to new and growing consumer markets (Krugman et al., 2012). Over time it has become increasingly more popular among firms and world production has fragmented from local production lines into long and complex global value chains (GVCs). For developing countries this provided a chance to integrate into the world economy.

Since jobs in emerging economies are characterized by a greater number of routine tasks and a higher degree of labor intensity, the number of jobs that are put at risk by robotization is greater for these countries than for developed countries (Naudé, 2019). World Bank (2016) predicts that up to two-thirds of all jobs in developing countries are susceptible to automation. Concerns about robotization should therefore be addressed to emerging economies as well.

2.6.1 Technology and trade: allies or rivals?

Technology and trade are regarded as the two main determinants of labor market outcomes in developed economies (Autor et al., 2013). However, they are often difficult to disentangle both conceptually and empirically. As arguments based on historical cases often seem to validate that these forces are interdependent and mutually reinforcing, some people even believe that they are actually different facets of a common phenomenon. For instance, technological progress, by continuously lowering transportation and communication costs, has been a major cause of the dramatic increase in international trade over the past decades. In turn, globalization and economic integration have eased the diffusion of technology across borders (Dao et al., 2017).

Although it is a widely held and popular viewpoint, international economists generally disagree with the perception that growth in world trade was primarily driven by technological advances in history. Krugman (1995), for instance, argues that the improvements in transportation and communication technology were only a minor factor that contributed to the growth in international trade. He postulates that the main causes are in fact political in nature, such as the removal of trade barriers and other protectionist measures. From this perception, the upward trend in world-trade and globalization also become reversible, something that is supported by the more recent observation of a slowdown in world trade.

2.6.2 Technology and the fragmentation of production

Many different factors have been identified which contributed to the increase in world trade since the 1960s. One of those being the upward trend in the fragmentation of production. Firms increasingly started to break up and fragment their production processes across different locations. When different parts of the production process are performed separately, successfully communication becomes necessary across the multiple locations and parties involved. Advances in information and communication technology (ICT) have made it easier and less costly for firms to disseminate information and coordinate different activities across distances. This has thus facilitated the fragmentation of production. Fort (2016) provides empirical evidence on the relationship between these technologies and firm's fragmentation decisions. She estimated that between 2002 and 2007, firms adopting communication technologies were on average 3.1 percentage point more likely to fragment production activities across locations. Furthermore, the effect is increasing in the use of such communication technologies. Although the effect is stronger for domestic fragmentation, it also applies to its foreign counterpart (i.e. offshoring). Fort (2016) looked at the time-period spanning 2002-2007 and primarily focused on communication technologies, measured by the use of computer aided design (CAD) software.

2.6.3 Industrial robots and offshoring

Even though the forces of technology and trade have to some extent positively influenced each other in previous cases, the idea that they should always act as companions is crumbling. Previous research by Fort (2016) found that the adoption of CAD-software induced firms to make greater use of contract manufacturing services. This thus means that a positive relationship exists between certain communication technologies and offshoring. However, an important difference should be noted in both the time-period and the technology under study between previous research by Fort (2016) and those we are concerned with today.

Firms try to minimize production costs, which depends on the endowment of the different factors of production. Most of the previous technologies that affected world trade were not used as actual factors of production per se but rather facilitated the use of different configurations of production. By lowering coordination and transportation costs, they allowed firms to take advantage of lower labor costs elsewhere.

However, the technology we are concerned with, industrial robots, are an entirely different type of technology and can be actually used as factors of production in the production process of goods and intermediates. Dao et al. (2017) states that the tasks which are suitable for automation are also suitable for offshoring, which make robots and foreign workers competitors in terms of costs. Hence, a fall in the price of industrial robots directly shifts the production cost function and changes the endowment of both robots and foreign workers. As the location of production becomes more or less irrelevant when industrial robots are used in production processes, offshoring decreases.

2.6.4 Import- versus employment-perspective of offshoring

In the above discussion, we explain the possible negative effects of robotization on offshoring by focusing on foreign employment directly. However, most literature does not measure offshoring in terms of the employment shares of developing countries but rather as patterns in the trade of intermediate inputs. Now as robots allow for cost reductions and greater productivity, prices change and trade patterns shift accordingly. Furthermore, the effects of robotization on offshoring are theoretically ambiguous and its effect could in theory be positive. Analogously to its impact on labor markets, the effect of robotization on offshoring can be decomposed in two opposite effects. We will explain these in terms of both foreign employment and trade:

- *Substitution effect (-)*: Industrial robots increase the capabilities and competitiveness of producers in developed countries. This leads to a greater variety and lower prices of intermediate inputs that are domestically produced. Intermediate inputs that were previously imported from abroad can now be sourced domestically (i.e. are substituted). This lowers the demand for foreign inputs and decreases the total value of imported intermediates. If offshoring is measured as some function of imports, it will decrease accordingly. At the same time the global demand for domestic inputs rises and exports increase. In terms of foreign employment, this effect can be explained in the same way as the displacement effect previously discussed (when we were concerned with developed economies). If we assume that robots directly compete with labor in the production of specific tasks, then the demand for foreign workers decreases with the increasing capabilities and falling prices of industrial robots. Hence, offshoring decreases accordingly.
- *Output effect (+)*: The adoption of industrial robots into production processes expands the scale of production. This raises the demand for all inputs, including those sourced from abroad (i.e. imports). When more intermediate inputs are imported from abroad, offshoring increases (Artuc et al., 2018). To understand this effect in terms of foreign

- employment, we assume that robots replace foreign workers in some tasks but not all. This is presumable since robots are likely not capable or too expensive to perform all tasks. Now as robots increase output, the demand for labor to perform these residual tasks increases.

2.6.5 What about developing countries?

The increasing capabilities and falling prices of industrial robots have thus lowered the relative cost advantage of developing countries. Previously offshore tasks that are currently performed by low-skill workers in developing countries can now be executed by inexpensive robots at home. Hence, even though developing countries have not themselves started to invest in industrial robots at a large scale, their involvement in GVCs indirectly exposes them to automation by developed countries and they are thus not immune to experience some disruptive effects. This might have important implications for future production fragmentation, the current organization of production in GVCs and world trade in general. Rodrik (2018) states that since robotization has the potential to lower the importance of GVCs, this could hamper the further development of developing countries. As discussed above, some economic developments of recent time such as the decline in world trade and premature deindustrialization, might indeed pose bigger threats to developing- rather than developed economies. Two reasons could explain why developing countries are at greater risk to experience the negative effects caused by the increased adoption of industrial robots:

- Industries in developing countries are characterized by a higher degree of routine tasks and labor-intensity, compared to those of developed countries (Kinkel et al., 2015). As it is theorized that especially routine and labor-intensive tasks are prone to automation, the effects of industrial robots could be much greater for these countries.
- The bargaining power of labor in developing countries is very low, which makes it easier for firms to lay off foreign workers compared to those in richer countries. Informal employment is commonplace in most developing countries. Workers are considered informal if they work without a wage contract and are not covered by social security (or other forms of social protection). Informal labor markets generally operate outside the regulatory framework of a country and therefore not comply with employment protection regulation and minimum wage laws. According to Arias et al., (2013), the informal employment shares in most developing countries range between 40 and 80 percent of the total labor force. Furthermore, labor institutions, such as unions, are much weaker compared to those of developed countries.

Even though the impacts might be more severe for developing countries, research on the functioning of their labor markets is more difficult. This is so because workers in developing countries are not directly at risk of being replaced by robots in their domestic industries (i.e. the displacement effect) but rather by those installed in developed countries. Next to that, there is only limited data available on the labor markets of developing countries, primarily because of the large informal employment shares as discussed above.

Many developing countries started to partake in the world economy through their involvement in GVCs. The establishment of GVCs were a direct result of the decisions of firms to offshore parts of their production processes abroad. However, it is argued that industrial robots incentivize firms against fragmenting and moving their production processes abroad to lower-wage countries and, even more concerning, to bring activities back into the home country.

Automation is often assumed to be labor-augmenting technical change in economic models (Kinkel et al., 2015). Acemoglu (2003) showed that, using standard assumptions for endogenous growth and the profit-maximizing incentives of firms, long-run technical change is labor-augmenting (Harrod's neutral). Labor-augmenting technical change is captured by a function A(t), that increases with time in a production function of the form: $Y = F(A(t)L, K)$. In simple terms this means that automation changes the effective size of the workforce. Hence, higher levels of output can be achieved using the same amount of workers. Or in different terms, the same amount of output can be achieved using less workers. If the adoption of industrial robots means that less labor input is needed, then the choice for the location of production becomes less dependent on wage differences between developed and developing countries. This would inadvertently mean that the relative attractiveness of offshoring production activities to lower-wage countries diminishes. Making matters worse: the comparative cost-advantage of developing countries is already eroding due to the fact that labor costs in many of those countries have been on the rise over the past decade. A report by the Boston Consulting Group states that wages in China and Mexico have increased by 300% and 67%, respectively, between 2004 and 2014 (Sirkin et al., 2014). Hence, it can be said that the cost-benefit analysis with respect to offshoring is changing, which may induce companies to move production tasks that were previously offshored back into their home country. This is the reverse process of offshoring and is therefore logically called: reshoring. Labor costs being equal, firms prefer to have their production activities as close as possible to their main consumer market in order to take advantage of transportation costs and the greater proximity to their final customer base.

Reshoring would directly lead to the destruction of jobs in developing countries that were previously offshored from developed economies. Although many acknowledge that it is increasingly taking place, the debate on reshoring is still ongoing and considerable disagreement exists in the literature about how big and important this phenomenon actually is. The start of reshoring does not mean the end of offshoring and they will likely take place at the same time. Changing cost-structures and demand-factors will make some businesses choose against foreign investment. For others, proximity to the strong growing markets of emerging economies will be more important.

2.6.6 Levels of analysis
Whether industrial robots affect offshoring activity, can be approached from two major perspectives. These are from the perspective of the firm or from an industry-level perspective. Looking at it from different levels of aggregation can provide complementary insights into the impacts of new technologies. The results of studies that focus on the firm level often show contradicting findings as they largely depend on the specific characteristics of the firms being investigated. It is possible that the growth of one firm negatively impacts the growth of other firms, which makes it hard to generalize the results to higher levels of aggregation (e.g. the overall industry). At the industry-level, the possible opposite effects of different firms (both direct and indirect) are aggregated and therefore give a clearer picture of what is happening in the real world. Another benefit of focusing on the level of the industry is that policy prescriptions are most often directed towards specific industries. Therefore, an understanding of what happens from an industry-perspective gives policymakers insights needed for the identification of areas that need intervention and thus more directly benefits the design of technology-related-policies.

2.6.7 Previous literature on offshoring
The following is a description of previous studies that have looked at the effects of industrial robots on offshoring activity. The results from both firm-level and industry-level approaches to research are discussed.

Firm-level perspective
Previous research that looked at firm-level data found that the relocation of manufacturing activities to developing countries is predominantly determined by firm size, country, export orientation and industrial sector (Kinkel et al., 2015). Furthermore, other factors that play a role include batch size, product complexity and robot use. The larger the size of the company, the greater the financial and human capital that can absorb the costs of relocation investments. Larger companies are more often looking for ways to achieve greater economies of scale and this makes them more likely to expand their boundaries abroad. Besides that, larger companies are also more likely to have previous experiences with cross-border production and relocation activities (Kinkel et al., 2015). This is in line with theoretical models on firm internationalization: new firms start doing business in countries that are in cultural-proximity and pose little investment risk. Later, in order to exploit further efficiency and productivity potential, business is expanded into more distant markets.

Furthermore, firms operating in some industries, such as metals, more often relocate production activities abroad compared to similar-size firms in other industries. Firms that are export-intensive are also more likely to set up production activities abroad.

The choice of firms to automate production processes depends on the costs of substituting machines for labor and how wages change in response to this (Chiacchio, 2018). If the capital expenditures to install and operate industrial robots are less than the potential cost savings, industrial robots improve the comparative costs position of manufacturing in developed countries. Kinkel et al., (2015), using firm-level data on manufacturing companies from seven European countries, analyze the effects of the use of industrial robots on the propensity of firms to offshore production activities outside the EU. Kinkel et al. (2015) finds that companies that use industrial robots more intensively, relocate parts of their production activities abroad less frequently. Furthermore, these companies are more often able to realize economies of scale and therefore show significantly higher labor productivity. They subscribe this to industrial robots being better at realizing efficient production processes through shorter processing times, higher process quality and competitive economies of scale. Hence, competition logic would conjecture these companies winning market share from competitors that invest less in automation (Kinkel et al., 2015).

<u>Industry-level perspective</u>
There have been several studies that look at the effects of robotization on offshoring from an industry-level perspective.

- De Backer et al. (2018), looking at the most recent years of IFR data between 2010 and 2014, found a negative association between investments in industrial robots and the growth rate in offshoring activity for industries in developed economies. In particular, when the robot stock of an industry increases by 10%, the offshoring growth rate decreases by 0.54%. Besides that, this negative association increases with the labor intensity of the industry. The more labor intensive an industry, the more of total production costs is spent as labor costs and the more inclined the industry becomes to adopt industrial robots. Hence, all else equal, industries that invest more in industrial robots will offshore less activities abroad. The study does not find any statistically significant relationship for emerging economies.
- Carbonero, Ernst and Weber (2018) conducted a study on the impact of industrial robots on world-wide employment. They estimated that due to an 24% global increase in the number of industrial robots over a time-period spanning 2005 and 2014, employment in developed- and developing countries declined by 0.54% and 14%, respectively and 1.3% world-wide. They contribute this larger detrimental effect on developing economies to: limited labor market institutions, high informality, large share of employment in agriculture and a tendency of multinationals to re-shore production closer to home. They subsequently looked at the question if industrial robots reduce offshoring in developed countries. According to their estimates, the increase of industrial robots between 2005 and 2014 caused offshoring to decrease with 0.7%. Furthermore, they find that in developed economies, the industry-level of labor intensity does not affect the relationship between industrial robots and employment. In the case of emerging economies, the results are more mixed.
- Artuc et al. (2019) examine the impacts of robotization in the US on exports from Mexico to the US. The study uses Mexican export data at the local labor market level and constructs a similar “exposure to robots” measure as Acemoglu and Restrepo (2017). However, the measure concerns the degree that Mexican workers (in each local labor market) are exposed to industrial robots installed by the US. The results indicate a strong and robust negative relationship between exposure to US robotization and exports from Mexico to the US. They estimate that when the U.S. uses one extra robot per thousand workers, growth in exports per worker from Mexico to the U.S. decreases by 6.7%. These results suggests that the substitution effect of industrial robots on trade is stronger than its income effect.
- Krenz et al. (2018) find evidence for a positive relation between the degree of automation and reshoring. Manufacturing sectors that experience an increase in robot density equal

to one more robot per 1,000 workers is, on average, associated with a 3.5% increase in re-shoring activity.

2.7 Policy prescriptions

Technological development can have major implications for the future of labor markets and world trade. The assessment of the impact of technological progress and automation is important, particularly for deriving policy prescriptions and recommendations that help to maintain the efficient functioning of labor markets and the world economy for the benefit of society.

Industrial robots have the potential to dramatically change the economy in both positive and negative ways. Given that most advanced economies have experienced slow growth in productivity over the past decades, the potential of robots to increase productivity are welcomed without much opposition.

On the other hand, robots have become increasingly more capable to replace labor, including skilled workers. As robots likely reduce opportunities for labor, they could potentially disrupt labor markets. Some of these disruptions we have discussed are: technological unemployment, decreasing or slow-growing real-wages, job polarization and income inequality. Furthermore we discussed that these problems could be even worse for developing countries.

Although greater productivity and income could in theory improve the well-being of all members of society, the benefits will likely not be shared evenly without appropriate policies. A variety of such policies to address the issues arising from the increased adoption of industrial robots have been suggested in the literature.

To combat the negative impacts of industrial robots, different solutions and policy-prescriptions are proposed by the literature. These can be categorized in three main channels and all focus on redistributing capital's share of income (i.e. the profits of industrial robots) more evenly across society (Freeman, 2015).

- Trade unions: Through collective bargaining, trade unions could raise wages and gain for workers a share of the higher productivity. That is the traditional way how workers have sought to increase their wages. However, Freeman (2015) explains that this is an unlikely possibility since the influence of trade unions has weakened in most countries in the last decades.
- Redistribution of income: Governments could intervene and redistribute income from the owners of capital towards ordinary workers through redistributive tax policies. This is the method that was most often used in history for redistributing income within a society. It is therefore not surprising that most of these policies already go back centuries in time and have not been designed to deal with robots or technology specifically. However, they could be a solution to combat the decreasing share of labor in income, the widening of the wage gab and unemployment. As robots have been theorized to cause or exacerbate such issues, these policies still offer valid approaches for addressing these labor market concerns and help with sharing the benefits of industrial robots more evenly. We will discuss three of such policies: universal basic income, employment subsidies and guaranteed employment. Universal basic income is a policy that ensures a basic income for all citizens of a country and usually such that it raises everyone above a certain poverty line. The term universal means that it is available to everyone or only limited to certain criteria such as citizenship or age. Furthermore, it is unconditional so the recipients are not required to work or attend school, etc. The main drawback of this policy is its cost. However, since it is not dependent on many rules or conditions, it is easy and less costly to administer. Employment subsidies is another policy that provides cash-payments. However, unlike universal basic income it is conditional on work-status or other conditions and thus not available to everyone. The idea of such a policy is that it creates an incentive for and increases the rewards from work. The last one, guaranteed employment, provides payments in exchange for labor services. The advantage of this policy is that it keeps people in the labor force by directly subsidizing work. However, it is also complex to administer and could potentially trap people in low-wage jobs without

many options for career development and could therefore by itself distort the labor market (Furman and Seamans, 2018).

- Spread the ownership of capital: Let workers earn part of their incomes from capital ownership rather than from working. Freeman (2015) states that the key question that needs to be asked is: "who owns the robots?". If a group of workers are replaced by robots there are two scenarios: they themselves become the owners of these robots or someone else (i.e. their boss) does. In the case of the workers owning the robots, then although it would make them jobless, they would still get paid. As they now can spend all their time on leisure, these workers are clearly better off. However, if someone else owned these robots, the workers would lose their jobs and be without income. The owners of the robots will reap all the benefits of the robots. The distribution of income would shift from workers toward the owners of capital and although overall income might increase, the well-being of the average person declines. As labor's share of income has been declining in most countries, this is a cause for concern that the second scenario is happening around us. If workers become owners of the robots that replace them, they become recipients of capital's share of income and income becomes distributed more equally (income inequality declines). There are two main ways to spread the ownership of capital. The first one is for workers to, either by themselves or collectively, invest in either shares on the stock market or private equity. The second one is to directly make workers owners of their employing firms. This can be done by for instance; employee ownership trusts, making stock options a standard part in wage contracts, employee stock purchase plans and profit-sharing. According to Freeman (2015), employee ownership has the greatest economic benefit out of all the options discussed. If workers are owners of their firms, it incentivizes them to work harder. It has been shown that on average, firms providing options for employee ownership perform better than those who do not. It thus benefits the economy directly compared to the other policy prescriptions that deal with robotization and the falling share of labor income. Governments can help spread employee ownership by giving tax breaks or preferential treatment (i.e. in a procurement process) to firms providing such options.

In order to maximize the benefits and minimize negative consequences, expertise on industrial robots and other advanced technologies are needed. Some have proposed for governments to introduce new commissions or advisory functions such as a "technology office" to gather empirical data and oversee the effects of technological development on labor market outcomes. This agency could then be used by governments to aid in the decision making concerning new technologies, for instance through the assessment and evaluation of existing and new policy proposals (Furman and Seamans, 2018).

3. Methodology

3.1 Research approach

In order to estimate the effect of industrial robots on offshoring intensity, we will need to regress some quantitative measure of offshoring on a measure that captures the penetration of industrial robots in production processes. When doing this, we will need to control for the other factors that affect offshoring and the adoption of industrial robots as much as possible. The regression model thus takes on the form as equation (3.1).

$$offshore = \beta_0 + \beta_1 robots + \dots + \beta_n control_n + u \qquad (3.1)$$

To estimate these effects, this thesis adopts a similar country-industry level approach as the papers by De Backer et al. (2018) and Carbonero et al. (2018). The main variables, including their measures, are discussed section 3.2. Section 3.3 discusses the selection of control variables that are included in the analysis. Please note that Equation (3.1) is only a simplified representation of the actual estimation model. This estimation model, together with the functional forms of the variables, are discussed in section 3.4. The effects of industrial robotics on offshoring are estimated using the statistical software package Stata and a fixed-effects estimation method. A short description of fixed-effects is given in section 3.5. Section 3.6 concludes this chapter with a discussion on the drawbacks of the research approach.

3.2 Main variables

Since this thesis is concerned with estimating the effect of industrial robot adoption on intensity in offshoring, these constitute our main variables. The following section discusses how these are defined, measured and constructed out of other variables.

3.2.1 Offshoring index

Due to increased globalization over time, offshoring has become an important concept in international trade and economics. The exact definition, however, remains somewhat fuzzy as it is sometimes unclear if a particular business activity is to be labeled as offshoring. Castellani et al. (2013) define offshoring as: “a firm’s allocation of business activities to another country, either by obtaining goods and services from an unaffiliated foreign supplier or by investing in a foreign affiliate or joint venture”. Various proxies for measuring offshoring activities have been proposed by the literature although quantification, like its definition, remains problematic. Feenstra and Hanson (1999) developed an index that is often used to measure offshoring intensity and is called the offshoring index. This index equals the ratio of non-energy intermediate inputs that are imported from abroad over total non-energy intermediate inputs (i.e. the share of imported inputs in total production). It should be noted that this index has been the recipient of some criticism from several scholars as they raise questions if this index really captures the phenomenon of offshoring. However, one would assume that a higher degree of offshoring is associated with a substantial flow of imported intermediate goods and services. Even though it is understandable that the index fails to capture the concept precisely, it should give an indication on the offshoring intensity at the industry-level. When more production processes are moved to foreign markers, the greater the number of intermediate inputs that need to be imported into the country. Hence, offshoring activity directly relates to the international sourcing of intermediate inputs. De Backer et al. (2016) state that for OECD countries, the share of imports in total domestic demand is indeed correlated with offshoring and could therefore serve as a proxy for it. Therefore, in this research a choice is made to measure the industry-level intensity of offshoring using the offshoring index. To get data on offshoring we thus need to gather data on both non-energy imported intermediates and total non-energy intermediate inputs for each country, industry and year. For a discussion on the data sources that are used to construct our main and control-variables, refer to chapter 5.

3.2.2 Robot density
Until now, terms such as the adoption of industrial robots, growth in the robot stock and robotization have often been used interchangeably. What we intend to communicate with these terms is the extent to which industrial robots have "penetrated" production processes. To quantify this concept we could simply look at each industry's stock of industrial robots, for which data is readily available by the IFR (2018). However, this definition fails to capture the concept precisely. For instance, an increase in an industry's robot stock could be solely due to economic reasons (e.g. increasing demand, etc.) and thus does not necessarily mean that robots have become more prevalent in that industry. A better measure for robotization would be the robot density in terms of employment. This measure is widely used in the literature and is simply defined to be the number of industrial robots per thousand workers (Chiacchio et al., 2018; Graetz et al., 2015). Hence, when an industry's robot density increases, then on average more robots and less workers are used in the production of goods. Acemoglu and Restrepo (2017), that look at the effects of robotization on employment and wages, use the same definition of robot density as a measure of the extent to which workers are being "threatened" or "exposed" to robots. Not surprisingly, they call this measure: exposure to robots.

3.3 Control variables
In the literature review various factors were identified that were theorized to affect the offshoring intensity of industries (or in different terms, the offshoring decisions of firms). These could therefore serve as control variables in our analysis. However, in practical terms, not all of these can easily be accounted for. For a further discussion on why this is the case, please refer to section 3.7, that discusses the drawbacks of the research approach. The control variables that will be accounted for in the estimation model are: labor intensity, the average wage, year-dummies, country-trends and industry-trends.

3.3.1 Labor intensity
In previous literature, it is stated that the degree of labor intensity influences both the offshoring intensity and the adoption of industrial robots. Labor intensity refers to the relative proportion of labor, compared to capital, used in a production process of a good or service. The reciprocal of labor intensity is capital intensity. Hence, a labor intensive industry is necessarily non-capital intensive. The concept can therefore be quantified as the ratio of total labor costs (i.e. wages, salaries and other labor compensation) over total capital costs (i.e. purchase, rents or depreciation of capital equipment). However, since data on total capital costs is not widely available, labor intensity is often proxied by various other measures in the literature. Jinjarak and Nakoi (2011), for instance, measure labor intensity as the share of wages and salaries in value added. Carbonero et al. (2018), however, compute it as ratio of total employment over gross fixed capital stock (i.e. the number of workers per unit of capital stock).
The more labor intensive an industry, the greater the share of total production costs that is spent on labor, and the more can possibly be saved on labor-cost. Hence, the composition of tasks (routine/non-routine, etc.) and the possibilities for automation being equal, industries/firms with a higher degree of labor intensity should be more inclined to (1) take advantage of lower labor costs in developing countries by offshoring production activities abroad or (2) automate certain tasks at the domestic facilities, by adopting industrial robots.

In this thesis we compute labor intensity using a similar measure as Jinjarak and Nakoi (2011). Following the approaches of De Backer et al. (2018) and Carbonero et al. (2018), we include labor intensity in the regression formula both in interaction with robot density and as a predictor by itself. However, the functional forms of these two terms are different. When interacted with robot density, labor intensity is included by means of a dummy-variable that is independent of time. The reason for this is to avoid contemporaneous endogeneity (Carbonero et al., 2018). The values of this dummy variable are computed by comparing the actual values of labor intensity with the country average at one specific point in time. For this, the year 2003 is chosen as it is the earliest year for which data is available on all countries. Note that, since only a single year of data is used in computing the dummy variable, it is constant over time for each country-industry pair in the dataset. A different interpretation of the discussion above is that we assign each industry to belong to one of the following groups: labor-intensive industries and capital-intensive industries. The theory then becomes that the effects of robotization on offshoring are different for these two groups of industries. We can therefore think of labor intensity as moderating the relationship between the adoption of industrial robots and offshoring. As a predictor by itself, however, labor intensity takes on its actual, time-dependent values. More details about the procedures of the dummy coding and the functional forms of labor intensity can be found in section 3.4.

3.3.2 Average wage

Following, Carbonero et al. (2018) we will control for domestic wages in the estimation model. The average wage (i.e. labor cost per worker) is computed by dividing an industry's total labor compensation over total employment. As firms try to minimize production costs, an increase in an industry's average wage-level increases the likelihood that firms: (1) move production processes abroad and (2) replace labor with "cheaper" industrial robots. Notice the similarities of this effect with that of an increase in labor intensity. This is because both the average wage and labor intensity relate to (and are computed using) total labor compensation.

3.3.3 Year-dummies

Including year dummy variables, for all but one year, allows to control for time-specific effects affecting offshoring activity that are not controlled by the other explanatory variables. For instance, shocks to the economy with an impact restricted to certain time-periods, can be accounted for by adding year-dummy variables to the estimation model. Since the time-span of our panel data set includes the global financial crises of 2008, something that could contaminate the results, including year-dummy variables in the model seems good practice. Concerning the coefficient estimates of the regression analysis, including year-dummy variables lets the intercept differ across time.

3.3.4 Country- and industry-trends

As we will see country- and industry-characteristics are important determinants for explaining the offshoring intensity and robot density of industries. As we use a fixed-effects method to estimate the regression model, time-constant variables cannot be included simply by themselves (for a further discussion see section 3.6). Hence, the inclusion of country-dummies or industry-dummies is pointless by itself. However, it is possible to interact these dummies with variables that change over time, such as time-trends.
Time trends allow to control for exogenous increases in the dependent variable that are not explained by the independent variables. If two variables are trending in the same or opposite direction, it can lead to the spurious regression problem: drawing a false conclusion that a relationship exist between two variables simply because each is growing over time due to other unobserved factors (Wooldridge, 2017). Time-trends can be accounted for by including a time index as an explanatory variable in the estimation model. An exponential time-trend (i.e. a time-trend with a constant growth rate) can be included by adding a linear trend to a model in which the dependent variable is in logarithmic form (Wooldridge, 2017).
Following Graetz and Michaels (2015), we include country-trends and industry-trends to the estimation model. With this we mean interaction-terms of time-trends with country- and industry-dummy variables, respectively. Country- and industry-trends thus capture time-trends that are specific to a country or industry.

3.4 Regression model

The final regression equation is given in equation (3.2). Note that, while the meaning of the terms should be clear from the discussions, the subscript notation for the year-, country- and industry-dummies are not entirely correct. In actuality, each particular year, country or industry would have its own designated dummy variable. However, doing this would make the equation unnecessarily messy.

$$log\left(1+offshore_{ict}\right) = \beta_0 + \beta_1 log\left(1+roboden_{ict}\right) + \beta_2 log\left(roboden_{ict}\right) \cdot d\left(labi_{ic2003}\right)$$

$$+\beta_3 log\left(1+labi_{ict}\right) + \beta_4 log\left(wage_{ict}\right) + \alpha_t d_t + \delta_c d_c \cdot t + \gamma_i d_i \cdot t + a_{ic} + u_{ict} \qquad (3.2)$$

<u>Dependent variable:</u>

$offshore_{ict}$ is the offshoring index for industry i, country c and year t.

<u>Independent variables:</u>

- $roboden_{ict}$ is the robot density of industry i, country c and year t.
- $labi_{ict}$ is the labor intensity of industry i, country c and year t.
- $wage_{ict}$ is the average wage of industry i, country c and year t.
- d_t are year-dummies
- $d_c \cdot t$ are country-trends.
- $d_i \cdot t$ are industry-trends.

<u>Error terms:</u>

- a_{ic} is the fixed effect (or unobserved effect) for industry i, country c. The fixed effect represents all the unobserved factors that are constant over time and that influence the dependent variable $offx_{ict}$ (Wooldridge, 2017).
- u_{ict} is the idiosyncratic error (or time-varying error) for industry i, country c and year t. This is the part of the error term that is dependent on time. It captures the unobserved factors that change over time and that affect the dependent variable $offx_{ict}$ (Wooldridge, 2017).

3.4.1 Functional forms

The offshoring index, the stock of industrial robots, labor intensity and wages appear in logarithmic form in the regression equation (3.2). There exist multiple reasons for doing this, such as the following:

- When both the dependent and an independent variable appear in logarithmic form, the regression coefficient belonging to that variable becomes the elasticity of the dependent variable with respect to the independent variable. This is convenient because of the percentage-change interpretations of elasticities.
- The regression coefficients belonging to variables that appear in logarithmic form are also invariant to rescaling. Hence, the units of measurement of these variables do not influence the size of the coefficients and are thus unimportant.
- Strictly positive variables often have heteroskedastic or skewed distributions. Taking the logarithmic form of such variables, transforms their distributions into one that more closely resembles a normal distribution. Hence, by taking the logarithm of the dependent variable, the model more closely satisfies the assumptions of the classical linear model. The more the assumptions are satisfied, the better the estimation results.
- Furthermore, since a logarithmic transformation narrows the range of a variable, the estimates become less sensitive to outliers.

One drawback of using the logarithmic form of the dependent variable is that it becomes more difficult to predict the original variable. However, our main aim is to estimate the effects on the dependent variable and not necessarily predict its values in absolute terms.

Two variables, the offshoring index and labor intensity, were computed as fractions that take on values between 0 and 1. In these cases, the range of the variables will only be widened when taking the logarithm. Furthermore, we will see in chapter 5 that the offshoring index and robot density take on the value 0 for certain observations, albeit limited in number. For these two reasons, we have included the offshoring index, robot density and labor intensity in the model by means of the form log(1 + x). This transformation makes sure that the range of the variables does not blow up and that the transformation is defined for all observations. Wooldridge (2017) states that if data on a variable x contains relatively few zeroes, it is acceptable to use log(1+x) in the model but interpret its estimates as these were estimated using log(x). In our case, considering that for each variable the subset of observations that take on a value of 0 is small in size compared to the entire dataset, the percentage change interpretation of the coefficients should remain closely preserved when using log(1+x). The downside of using log(1+x) is that, although it is distributed less heteroskedastic than x, it can not be normally distributed. However, normal distribution is not a requirement for the estimation approach per se.

As discussed in section 3.3.1, when interacting labor intensity with robot density we include it in the form of a dummy variable. The steps for computing the dummy values are as follows. First, the labor intensity is computed for each country-industry pair in the year 2006. Then, the country's average labor intensity is computed for that same year. The values of the dummy variable now follow from the comparison of each industry's labor intensity with the country's average. Hence, industries characterized by a relatively high labor intensity, compared to other industries in the same country, obtain the value 1. Similarly, industries with a below national average labor intensity get assigned the value 0.

3.5 Fixed-effects estimation

The proposed model is estimated using a fixed-effect, pooled Ordinary Least Squares (OLS) method. A fixed-effect model estimates the parameters of the model by regressing the time-demeaned variables (i.e. the within transformation). By doing this, one degree of freedom is lost for every country-industry cluster.

A fixed-effects model splits the error term in two parts, such that each part is either independent- or dependent on time. In equation (3.2) these error terms are a_{ic} and u_{ict}, respectively. When the data is transformed (time-demeaned), the fixed-effect error term disappears and is therefore not of any concern. Hence, arbitrary correlation between a_{ic} and the explanatory variables is allowed in any time-period. The key assumption of a fixed-effects model is that the idiosyncratic errors are uncorrelated with each explanatory variable in all time periods. Hence, the explanatory variables should be strictly exogenous. However, since standard errors are two-way clustered at the country-industry level, they are robust against heteroskedasticity or serial correlation of the idiosyncratic errors.

One downside of fixed-effects estimation is that, besides taking care of the fixed-effect error term, this will also lead to the cancelling out of other time-constant factors. In other words, any explanatory variable that is constant over time is cancelled out by the within transformation and cannot be estimated (Wooldridge, 2017). However, since we are primarily concerned with the change of variables over time (i.e. how a change in the stock of industrial robots affects offshoring activity) this is not of major concern.

As we do not have the same time-periods for all clusters, it concerns an unbalanced panel. If the reason that the data is missing for some observations is not correlated with the idiosyncratic errors, than an unbalanced panel dataset causes no problem for estimating the parameters with fixed-effect estimation. In other words, the unbiasedness and consistency of the estimators are not affected. In our case, the reason that the panel is unbalanced is that one or some of the data sources did not or could not collect the data for specific country-industry pairs in certain years. Hence, if we assume that this is not correlated with the idiosyncratic errors, our unbalanced panel does not cause problems. Standard errors are adjusted by clustering at the country-industry level. As the number of clusters in our dataset is fairly large, there is no major concern for the validity of the clustering approach and thus for the approximation of the confidence intervals and critical values. One possible downside is the fact that the clusters are unbalanced. However, as the variation between the size of the clusters is fairly minimal, this should not be of major concern.

3.6 Drawbacks

The chosen research approach has a couple of drawbacks attached to it. The first one is that in the analysis we use a proxy of offshoring activity that is known as the offshoring index. This index is computed as the share of total intermediate inputs that are imported from abroad. However, as discussed in section 3.2.1, this measure did receive some criticism on its ability to accurately measure the concept. Instead of using the offshoring index, one could use other measures to capture offshoring activity, such as bilateral trade data between separate pairs of countries, as can be found in input-output databases. This, however, increases the complexity of the analysis and considering the time-constraint were not an option for this thesis.

In the literature review, we identified various factors that are, like the adoption of industrial robots, theorized to affect the offshoring activity of an industry. The most notable ones include: the increasing demand for services, increasing demand for customization features, rising labor costs in developing countries (e.g. China and India) and increasing protectionism and trade barriers. In order to account for these factors they should be included as control variables in the estimation model. However, some of these factors concern fairly abstract concepts, such as the demand for customization features and protectionism. It seems implausible that these concepts lend themselves to reliable measurement on a quantitative scale from either a global, country or industry level. Other factors, such as the demand for services and rising labor costs in developing countries could in theory be accounted for. For instance, it is possible to include in the model, depending on the specific industry, the labor costs of a group of developing countries, either separately or as a weighted average. However, this will greatly increase the complexity of the research method. Therefore, due to the time limitations of the thesis project, these factors will not be included in the estimation model. However, the inclusion of time-trends allows us to control for variables that are trending over time for reasons related to other unobserved factors. Hence, even though some important variables are omitted from the analysis, it is possible that some of these factors are captured by either year-dummies (time-specific events) or time-trends (variables that grow with time).

There exist sources of potential endogeneity, which pose a threat to the internal validity of the research design. The two major ones that cannot be ruled out are:

- There might be unobserved time-varying effects (secular sectoral trends) that affect the dependent and independent variables, either globally or in a specific country or industry. For instance, offshoring activity and the adoption of industrial robots could be affected by the business cycle or other transitory-fluctuations.
- Another issue is that of reverse causality, as it is possible that the reverse relationship holds true in nature (i.e. that changes in offshoring activity affects the adoption of industrial robots). For instance, industries that are facing higher import competition from abroad may be more inclined to adopt industrial robots in order to become more competitive (Artuc et al., 2019). Furthermore, increased barriers to trade or labor-costs in developing countries might increase the costs associated with offshoring and make firms less willing to move production processes abroad. This might induce them to invest more heavily in industrial robots and automation at their domestic facilities. As we hypothesize that the increased adoption of industrial robots leads firms to offshore less production activities abroad, we would ideally test for a casual relationship. However, the estimation of our model only allows to test for correlational relationships.

The first issue of potential endogeneity can be minimized by either including year-dummies in the estimation model or by regressing the long-run trends of the variables (Karabarbounis and Neiman, 2013). Both these methods decrease the influence of temporary shocks in the estimation of the regression coefficients. The second issue can in principal be tackled by using an instrumental variable approach. Carbonero et al. (2018), for instance, instrument the stock of industrial robots with an index of technological progress (TP) of robots at the country level. The higher the TP index, the greater the capabilities of industrial robots to perform different tasks. This index allows to distinguish between the adoption of industrial robots due to technological progress and adoption due to capital deepening. Another example is by Artuc et al. (2019) that, although focusing on Mexican exports to the US, use an instrumental variable approach taking into account the robotization patterns of Europe. Changes in the stock of industrial robots are highly correlated between Europe and the US. However, Mexico's trade with Europe is only small-scale compared to that with the US. Hence, productivity- or price-changes in Mexico's industries are unlikely to affect the adoption of industrial robots in Europe. So if a change in robotization occurred in both the US and Europe, the problem of reverse causality can be ruled out with high probability. Again, time constraints did not allow us to implement these higher quality but more complex methods in the analysis.

It should also be noted that it is possible that the size of the effect were are trying to estimate is small in the population model. Industrial robotization might only be in its infant stages and based on data currently available, it may be a difficult tasks to observe or estimate the effects in full. This will be discussed further in the discussion.

4. Data

4.1 Data sources

In order to construct a panel dataset, containing data on all the relevant variables included in our estimation model given by equation (4.2), we will utilize three main data sources. These will now be discussed in turn.

4.1.1 Organization for Economic Co-operation and Development (OECD)

The Organization for Economic Co-operation and Development (OECD) is an intergovernmental economic organization (IGO) that currently consists of 36 member countries. The organization is headquartered in Paris, France and was officially founded in 1961. However, the organization first originated as early as 1948 as the Organisation for European Economic Cooperation (OEEC). In 1961, the OEEC was reformed into the OECD, extending membership to non-European countries. The organization's goal was to boost world trade, economic growth, prosperity and sustainability by working together to understand what drives economic, social and environmental change.

Its members are primarily high-income, developed countries that share a commitment to the market economy and personal democracy. Currently, its member countries together account for 63% of global GDP, 75% of world trade, over 50% of the world's energy consumption, 18% of the world's population and 95% of world development assistance (OECD, 2019). A list of current OECD member countries is given in table 4.1.

OECD Member Countries (2019)		
Australia	Hungary	New Zealand
Austria	Iceland	Norway
Belgium	Ireland	Poland
Canada	Israel	Portugal
Chile	Italy	Slovakia
Czech Republic	Japan	Slovenia
Denmark	Korea	Spain
Estonia	Latvia	Sweden
Finland	Lithuania	Switzerland
France	Luxembourg	Turkey
Germany	Mexico	United Kingdom
Greece	Netherlands	United States

Table 4.1: List of OECD member countries

The OECD serves as a forum to find solutions to common socio-economical problems, identify best practices and coordinate various domestic and international policies. In general terms the OECD functions as follows: (1) the OECD Secretariat collects and analyses data, (2) committees discuss the findings and possible policies, (3) the Council makes decisions and (4) governments implement the recommendations.

The OECD collects data on numerous economic, social and statistical variables, such as, productivity (GDP), employment and global flows of trade and investment. In order to do this the organization collaborates with representatives of governments, international organizations, businesses, trade unions and other institutions. The gathered data is subsequently analyzed and studied for which the results are published in economic reports and scientific articles. Besides that, the OECD is involved in the establishment of international norms and standards, most notably on tax, education, agriculture and the safety of chemicals. Most of OECD's data is made available on the internet for free in internationally comparable format. For this study, we will make use of two OECD datasets, which will be discussed next.

4.1.2 Structural Analysis Database (STAN)

The STructural ANalysis Database (STAN) is a database that includes data on a variety of variables such as gross output, value added, labor input, investments and capital stock. The data is given for a country-industry level on an annual basis from 1970 onwards. STAN, like other OECD databases, uses a standard industry classification based on the International Standard Industrial Classification of All Economic Activities revision 4 (ISIC rev4). STAN's data is constructed primarily based on member countries' annual national accounts but it also consults other sources such as the results from national business surveys. Data on an industry's total intermediate inputs can easily be accessed in OECD's STAN database. Data on both wages and salaries and value added are included in OECD's STAN database.

For each country, the following variables are imported from OECD's Structural Analysis (STAN) database:

- INTI: Intermediate inputs, current prices
- VALU: Value added, current prices
- LABR: Labor costs (compensation of employees), current prices
- EMPN: Number of persons engaged - total employment, thousands.

4.1.3 Bilateral Trade Database by Industry and End-Use (BTDIxE)

To get data on imported intermediates we consult a different OECD database named the Bilateral Trade Database by Industry and End-Use (BTDIxE). BTDIxE is a database that solely focuses on data on the international trade flows of intermediate goods for over a hundred countries, including all OECD members. The data is expressed in nominal terms and published in the form of time-series. The database is constructed using data from the United Nations Statistics Division's (UNSD) Comtrade Database and also uses historical data from the OECD's International Trade by Commodity Statistics (ITCS). For each pair of country and partner country, the values and quantities of imports and exports are broken down by industrial activities based on ISIC rev4 and divided into three main end-uses: intermediate inputs, household consumption and capital goods. Hence, to find data on imported intermediates for a specific country-industry combination, we select the entire world as a partner country and look for intermediate goods in the BTDIxE database.

4.1.4 International Federation of Robotics (IFR)

The International Federation of Robotics (IFR) is an organization that gathers primary data on industrial robot installations by country, industry and application on a yearly basis from 1993 until 2015. Nearly all industrial robot suppliers worldwide, directly report to the IFR Statistical Department. Besides that, the IFR collects secondary data from several national robot associations on their national markets. For instance, the Japanese Robot Association (JARA) provides data to the IFR on worldwide robot shipments by Japanese supplier companies. The secondary data is mainly used to validate the primary data and ensuring that data quality is met (International Federation of Robotics, 2018).

The annual data provided by the IFR consists of both the stock (total installations) and the flow (total orders) of industrial robots for all industries in each country. Flow values refer to the total accumulated annual sales (year total orders/shipments) of industrial robots by a particular industry. Robot stock is an estimate of the total installed and operational robot stock where depreciation is taken into account. Assumed is that on average an industrial robot has a service life of 12 years and is immediately withdrawn from service afterward. Both sales and stock are denominated in units, hence the value and quality of the robots are not taken into account.

Some previous research which used data provided by IFR, such as Graetz and Michaels (2015), assume a different depreciation rate for industrial robots than what is used by the IFR. Therefore, stock data is used only for the first year of analysis and for later years the stock of industrial robots is computed using flow data and the chosen depreciation rate. In this research we have chosen to assume the same depreciation rate as the IFR and therefore only use the data on the stock of industrial robots. In calculating the operating stock of robots, it is assumed that the average operating service life of an industrial robot is 12 years.

There exists a couple of shortcoming with the data provided by the IFR. In the data manipulations and transformations section explains how these issues can be dealt with. The three most important drawbacks of IFR data are:

- Unspecified: Even though, for most years in the time period spanning 1993 and 2015, IFR reports the total stock of industrial robots for the countries in the dataset, they are often not classified in terms of the industries that installed them. In the IFR dataset these are simply listed under a class called: Unspecified. This is especially a problem for earlier years where for most countries the total stock of robots equals what is listed under unspecified. However, also for later years, the share of total robots that are listed under unspecified can be large for some countries.
- North America: For years prior to 2011, the IFR only reports data for Canada, Mexico and the United States combined.
- IFR classes: The categories used to break down industry-level data by the IFR do not exactly correspond with the OECD datasets. The big difference is that IFR classes are more aggregated in the services industries and more disaggregated in the manufacturing industries, particularly the automotive and electronics industries. The IFR extended the number of industrial branches to be surveyed to satisfy the need for a deeper analysis of the distribution of industrial robots (IFR, 2018). Besides that, it is to be expected that data can be obtained more precisely for industries that invest more heavily in industrial robots. The good news is that, the IFR classes are still based on the same ISIC Rev.4, so considerable correspondences exists and a method of conversion is provided in the International Federation of Robotics (2018).

4.2 Sample selection

We are concerned with how robot adoption in developed countries affects offshoring activity and thus developing countries through their involvement in global value chains. Given the fact that all OECD member countries are classified as developed and that the OECD makes data available on various variables for its member countries, the collection of all OECD members serves as a good starting point for sample selection. In principle all member countries will be included in our dataset. However, for some countries either data is not available for all relevant variables or data is only given for a limited number of years. Hence, for reasons due to data limitations, eight countries were omitted from our original OECD sample. These countries, together with the reason for omitting them, are given in table 4.2.

Country:	Reason:	Specific:
Chile	Incomplete STAN data	Data only available for limited years and industries.
Estonia		Values for intermediate inputs (INTI) and value added (VALU) are missing for most years.
Iceland		Data only available for limited years and industries.
Israel		Only three years of data available on all STAN variables.
Latvia		Data only available for limited years and industries.
Switzerland		Labor costs (LABR) is not included in the dataset.
Turkey		Data on intermediate inputs (INTI) is only given for the year 2012.
Luxembourg	Missing IFR data	No data is published by the IFR on the stock of industrial robots.

Table 4.2: Omitted countries from the OECD sample

4.3 Data manipulations and transformations

4.3.1 Currencies

In OECD's STAN dataset all nominal values are listed in foreign currency and current prices. In BTDIxE, however, all values are listed in U.S. dollars, current prices. In the data analysis we will use variables that are compositions (ratios) of the variables found in these datasets. To calculate the labor intensity we take the ratio and only use data from the STAN dataset. It therefore does not matter if we first convert the values to U.S. dollars or not, since the exchange rate would cancel out anyway. The offshoring index, however, is computed as the share of total intermediate inputs that are imported from abroad and thus uses data from both datasets. We therefore need to convert each value of total intermediate inputs (INTI) to U.S. dollars. Since we need to do this for at least one variable obtained from the STAN dataset, we have chosen to convert all the nominal variables to U.S. dollars. This also improves the comparability between countries and allows the variables to be summed over countries. To convert all nominal values (current prices) of the variables obtained from OECD's STAN dataset to U.S. dollars (current prices), we need to make use of exchange rate data. To do this we make use of OECD's exchange rate dataset (retrieved from: https://data.oecd.org/conversion/exchange-rates.htm). For each country, this dataset contains the exchange rate, expressed as foreign currency per U.S. dollar, for all years from 1950 to 2018. We first merge OECD's STAN dataset with the exchange rate dataset. Then, to express the values of INTI, VALU and LABR in current U.S. dollars, we divide each of these variables with that year's exchange rate.

4.3.2 North America before 2011 (Canada, Mexico and the United States)

As explained before, the IFR only records industry data on the stock of industrial robots for North America as a whole for years prior to 2011. In the IFR dataset, pre-2011 data for Canada and Mexico are included in those of the United States. To overcome this problem, only North America is included in the data analysis for years prior to 2011. From the year 2011, data on each of the three countries are included separately. Therefore, in total our dataset consist of 29 “countries”: 28 member countries of the OECD and North America.

In order to do this we need to correctly match the three datasets again. In the IFR dataset, we simply rename the United States to be “North America” for years prior to 2011. Besides that, we delete pre-2011 data for Canada and Mexico which are listed with a value equal to 0 in the dataset. STAN and BTDIxE only list data for Canada, Mexico and the United States separately. To match these with the IFR data, we need to sum the values for all variables over the three countries (STAN: INTI, VALU, LABR and EMPN, and BTDIxE: imports). After the conversion of all relevant nominal values from foreign currency to U.S. dollars using the appropriate exchange rates, all the variables lend themselves to being summed over different countries.

4.3.3 Classification of industries

Like most industry-level economic data, the three datasets we will use in our analysis break down their data based on an industry classification known as ISIC Rev. 4. However, even though many correspondences exists, the exact classification of industries that is used by the three datasets is somewhat different. The major difference between them being the level of aggregation.

The industry classification used in the IFR dataset differs mostly from the other two. However, even the STAN and BTDIxE datasets, although obtained from the same source (OECD), also have minor differences between them. Hence, in order to consistently match all data sets, we will need to re-classify the data where necessary. The good news is that for the rest, after aggregating some industrial data in each of the three datasets, the different classifications do not differ by much.

To do this we will retain to the industry classification of the STAN dataset as much as possible as it most closely matches the classes of ISIC Rev.4 itself. We will then proceed to match the BTDIxE and IFR datasets accordingly. To match our datasets we first re-classify the IFR classes to ISIC Rev. 4 using the conversion/correspondence table given in International Federation of Robotics (2018) and aggregate the data where necessary. The bad news of this is that we can not take advantage of the more disaggregated data on manufacturing industries by the IFR.

After merging the STAN, BTDIxE and IFR datasets, we have a dataset containing 29 countries and 15 industries. Although the panel dataset is unbalanced, the period ranges from 1993 to 2015. Table 4.3 gives the classification of industries that is used in the regression analysis. Refer to appendix A.1 for the correspondences of this industry classification with those of the STAN, BTDIxE and IFR datasets, respectively.

Industry Classification (ISIC Rev 4.)		
Id	**Code**	**Name**
TOT	*01-99*	Total
MANU	*10-33*	Manufacturing [C]
1	*01-03*	Agriculture, hunting, forestry and fishing [A]
2	*05-09*	Mining and quarrying [B]
3	*10-12*	Food products, beverages and tobacco [CA]
4	*13-15*	Textiles, wearing apparel, leather and related prodcuts [CB]
5	*16-18*	Wood and paper products, and printing [CC]
6	*19-23*	Chemical, rubber, plastics, fuel products and other non-metallic mineral products
7	*24*	Basic metals
8	*25*	Fabricated metal products, except machinery and equipment
9	*26*	Computer, electronic and optical products [CI]
10	*27*	Electrical equipment [CJ]
11	*28*	Machinery and equipment n.e.c. [CK]
12	*29*	Motor vehicles, trailers and semi-trailers
13	*30*	Other transport equipment
14	*31-33*	Furniture; other manufacturing; repair and installation of machinery and equipment [CM]
15	*35-99*	Total services and other activities [D-E] [F] [G-U]

Table 4.3: Classification of industries

4.3.4 Unspecified (IFR)

As explained before, the problem of industrial robot stock that IFR reported as unspecified is especially evident for earlier years. However, it depends on the country how big this problem is and from what year IFR does start to classify its data to specific industries. In the case of Japan, for instance, all data is specified by industry starting from the first reporting year of the IFR. In figure 4.1, we have plotted the size of unspecified together with the total stock for North America. We see that for North America, until the year 2003, all stock of industrial robots were reported under unspecified.

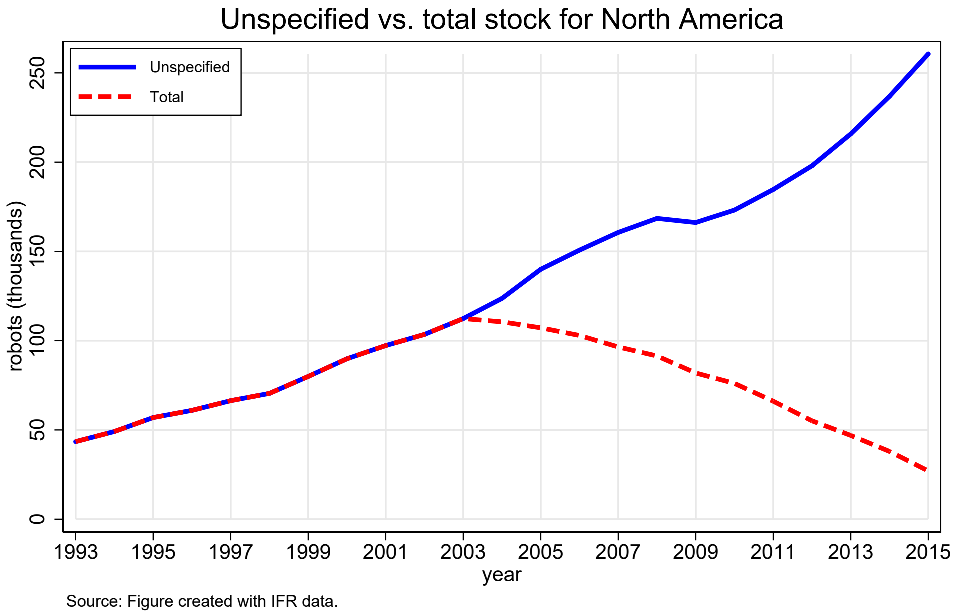

Figure 4.1: Unspecified

To deal with the problem of unspecified we will follow a similar imputation method as used by Graetz and Michaels (2015) in order to redistribute each year's value of unspecified among industries. In order to do this, for each country-industry pair separately, we look for the first year that the IFR assigned data to that specific industry, let's call it year A. In other words, year A is the first year for which that industry's total stock of industrial robots becomes greater than zero.

Then for all years after year A, we compute the share of specified robots in that country (total robots - unspecified) that were assigned to that industry. Next, we calculate the average of these "robot" shares over all years later than year A. This averaged value is then assigned to be the "robot" share for years prior to year A. Lastly, we multiply the value of "robot" share with each year's total robots stock. This value is assigned to be that industry's stock of industrial robots in that specific year. Note that we computed the share using *total robots - unspecified* but calculated the new value of robot stock by multiplying with *total robots*. Hence, even for years later than year A, the stock of industrial robots has changed since we assigned some robots that were previously listed under unspecified belonging to this industry. By doing this we made the assumption that the robots listed under unspecified are "random" in the sense that they belong to industries in the same way as the robots which are specified do.

4.4 Variables

So far this section described the different data sources and the variables they contain that are important to construct the final dataset. Before that, we discussed the regression model and how the dependent and independent variables were to be constructed or measured. Table 4.4 connects both of these sections and gives a quick overview of how each variable in our model is constructed and what data sources are used for this.

Abbreviation	Name	Formula	Sources
offshore	Offshoring index	Imports / Intermediate inputs	Imports: BTDIxE Intermediate inputs: STAN
roboden	Robot density	Robot stock / Total employment	Robot stock: IFR Total employment: STAN
labi	Labor intensity	Labor costs / Value added	Labor costs: STAN Value added: STAN
wage	Average wage	Labor costs / Total employment	Labor costs: STAN Total employment: STAN

Table 4.4: Construction of variables

5. Descriptive statistics
5.1 Tables
Table 5.1 presents the descriptive statistics for all variables included in the analysis. Although most variables appear in logarithmic form in the model, the statistics for both the level- and logarithmic-form of the variables are given. Appendix A.2 provides the descriptive statistics for specific industries in separate tables. Furthermore, in appendix A.3 one can find figures that graphically display the distribution of the variables in the dataset by means of a histogram and kernel density estimation plot.

Descriptive Statistics Full Dataset										
Variables	**N**	**Mean**	**Standard Deviation**	**Min**	**First Quartile**	**Median**	**Third Quartile**	**Max**	**Skewness**	**Kurtosis**
offshore	8091	1.285	5.410	0	0.137	0.386	0.728	119.374	10.989	154.888
roboden	8091	6.672	20.052	0	0.047	0.874	4.669	473.85	8.083	107.759
labi	8091	0.553	0.200	0.035	0.458	0.564	0.661	8.502	8.457	323.003
wage	8091	36.124	24.774	0.446	15.784	33.258	51.052	274.056	1.061	5.639
log(1+offshore)	8091	0.462	0.571	0	0.128	0.326	0.547	4.791	3.337	17.287
log(1+roboden)	8091	1.048	1.171	0	0.046	0.628	1.735	6.163	1.201	3.856
dummy(labi)	8091	0.567	0.495	0	0	1	1	1	-0.272	1.074
log(1+labi)	8091	0.433	0.118	0.034	0.377	0.447	0.507	2.251	0.042	12.169
log(wage)	8091	3.272	0.918	-0.808	2.759	3.504	3.933	5.613	-1.062	4.07

Table 5.1: Descriptive statistics based on the full dataset

<u>Offshoring index</u>
We notice that the offshoring index has a mean value of 1.285 with a standard deviation of 5.410. This seems implausible as the offshoring index is a scalar quantity defined as the ratio of imported non-energy intermediate inputs over total non-energy intermediate inputs. Its dimensionless values are therefore supposed to range between 0 and 1. However, notice that even the value for the third quartile (0.728) is much smaller than the mean. Hence, the distribution for the offshoring index is positively skewed.
It seems to be the case that some outliers have considerably increased the mean and standard deviation of the offshoring index. Looking at the descriptive statistics tables for specific industries in appendix A.2, we observe that this problem arises in multiple industries (namely, 10 out of the 15). To check if nothing went wrong during: importing the data, transforming the data or in constructing the variables themselves, we manually computed the offshoring index for certain observations using the original sources. The results we got were the same as those listed in the dataset. Directly inspecting OECD's STAN and BTDIxE databases, we learn that the values for imported non-energy intermediate inputs do indeed exceed total non-energy intermediate inputs for some observations. Upon closer inspection of the OECD's databases, it seems to be the case that STAN and BTDIxE define intermediate inputs somewhat differently. In actuality, the BTDIxE database calls it intermediate goods rather than inputs. This variable might include a greater range of goods, which would explain why the imported value can exceed the total and hence, why the offshoring index exceeds 1 for some observations. If this problem arises with the same probability for each observation, we would not worry too much about it. However, considering that this problem arises in particular for certain industries, it might affect our results considerably. For one industry this problem seems exceptionally large, which is the *Mining and quarrying* industry. For this industry, the mean value of the offshoring index is 11.48 with a standard deviation of 17.183. Therefore, in running the

regressions, we will leave certain industries out of the analysis and see how this would affect our results.

Robot density

The mean value for the density of industrial robots is 6.672, which is expressed in units of robots per thousand workers. Its standard deviation is 20.052. Since the mean is much greater than the third quartile, its distribution is heavily skewed to the right. Looking at the descriptive statistics tables for specific industries in the appendix, we observe that the skewness of the distribution is caused in particular by the industry *Motor vehicles, trailers and semi-trailers*. For this industry, the stock of industrial robots is distributed with a mean of 46.404 and standard deviation 55.611. Previous literature indeed stated that this industry accounts for the greatest concentration of industrial robots.

Labor intensity

The mean value for labor intensity is 0.553 with a standard deviation of 0.200. As this variable is computed by dividing two monetary variables, it is dimensionless in nature. Labor intensity was measured as the share of wages and salaries in value added and it seems unrealistic that the value of wages exceed value-added. However, we do observe that the maximum value of labor intensity is 8.502. Inspecting our dataset, we find that for a limited number of observations (country-industry pairs) the value of labor intensity exceeds one. Furthermore, this problem arises not for any country or industry in particular but fairly at random. Examining OECD's STAN database directly, we detect this phenomenon also in the actual data. This problem did therefore not arise from our data manipulations but was inherited from the original source.

Wages

The mean value for average wages is 36.124 with a standard deviation of 24.774. The units of this variable are in thousands US dollars per employee per year. Like the previous variables we discussed, its distribution is highly skewed to the right.

Logarithmic values

In section 3.4.1, we discussed that in the regression equation (3.2), none of the variables actually appear in level-form. The offshoring index, the stock of industrial robots and wages appear in logarithmic form. The first three variables were all strictly positive with distributions that are highly skewed to the right. We have also discussed some benefits of including a variable in logarithmic-form in the estimation model. One of these was that after a logarithmic transformation, the distribution of a variable more closely resembles a normal distribution. This can be observed from the descriptive statistics table 5.1. For the variables log(offshore), log(1 + robots) and log(wages), the mean lies more closely to the median and in all cases between the first and third quartiles. Furthermore, labor intensity is included by means of a dummy variable. The reason for including labor intensity as a dummy variable, computed using a single year of data, is that otherwise issues due to contemporaneous endogeneity can arise (Carbonero et al., 2018).

5.2 Figures

To better understand the data, the following discussion presents some figures that graphically display the important variables over time and across industries/countries. Even though Canada, Mexico and the United States are included in the dataset separately from 2011 onwards, the data for these countries have been aggregated for all years in the following section and grouped under North America. This choice to only include North America was made to improve the readability and comparability of the figures and tables. However, the United States is by far the largest contributor of data on North America, so one could approximate it as such.

5.2.1 Industrial robots by country

Figure 5.1 graphically displays the total stock of industrial robots over time for selected countries from our dataset. The reason the figure is limited to France, Germany, Italy, Japan, Korea, North America and the United Kingdom is that otherwise the display would become too messy.

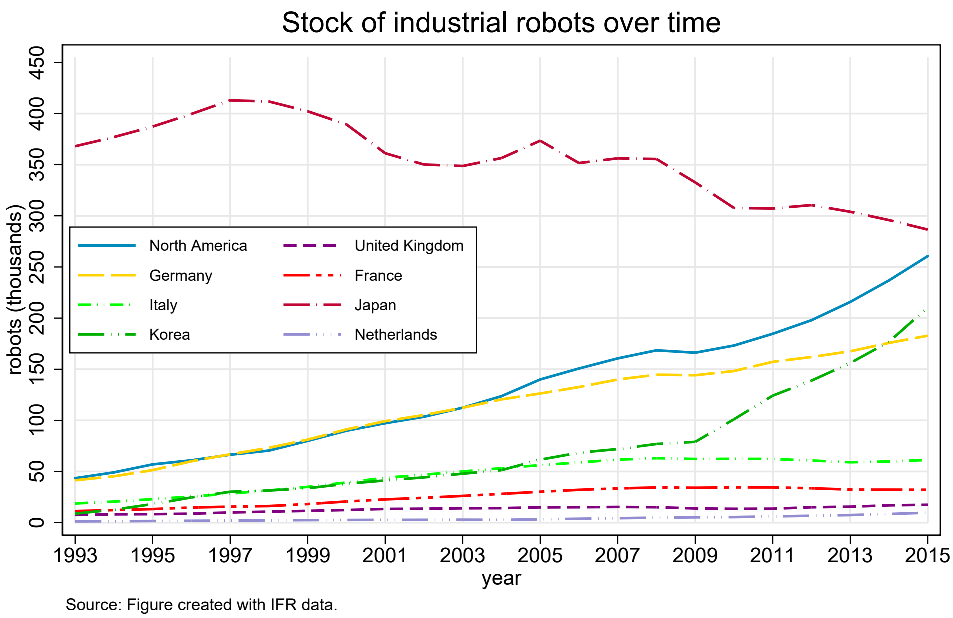

Figure 5.1: Robot stock

Looking at the figure we see that there exist a lot of variation in the use of industrial robots between countries. Japan is observed to be the biggest user of industrial robots during the last decades from a global perspective. However, Japan is also the only country for which the stock of industrial robots decreased over the time-period 1995-2005. More recently North America, Korea and Germany have been catching up with Japan in terms of installing industrial robots. It is not surprising, however, that these countries have bigger stocks of industrial robots compared to other countries in the dataset, as these are also the biggest countries in terms of population and GDP. All else equal, the bigger a country's industries, the more industrial robots one expects to be installed. Looking at the stock of industrial robots therefore does not really say anything about the extent to which a country has adopted industrial robots.

To compare the adoption of industrial robots between countries, it is better to look at the robot density in terms of employment. Figure 5.2 depicts the robot density over time, calculated over all industries combined, for the same selected countries as figure 5.1.

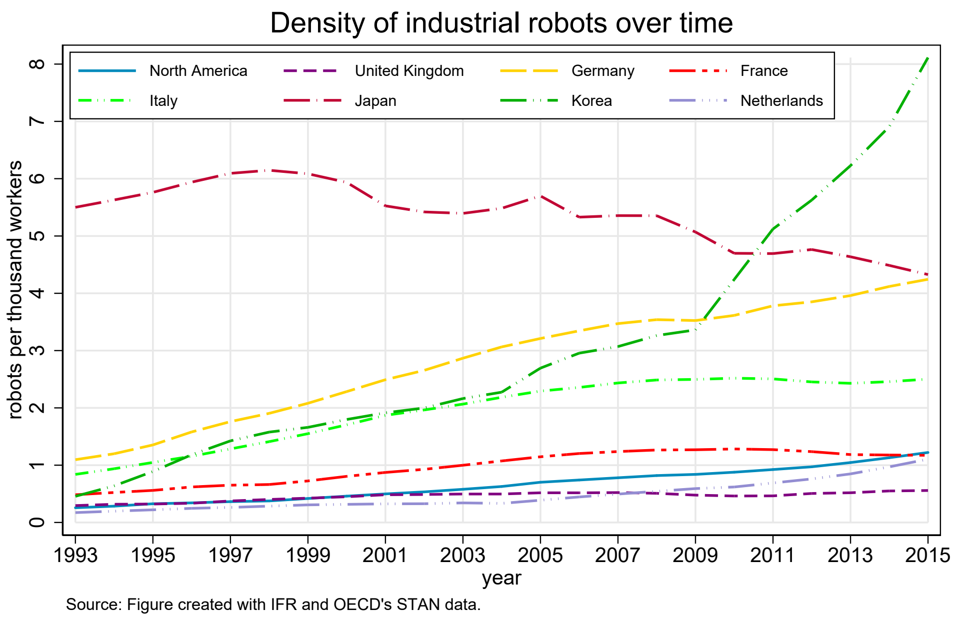

Figure 5.2: Robot density

From this we see that the adoption of industrial robots is becoming especially prevalent in countries like Korea and Germany, that either already passed or will in the near future pass Japan in terms of robot density. In 1995, every thousand Korean workers were exposed to 0.9 industrial robots on average. By 2015, this number had increased dramatically to about 8. As a comparison, in 1995 every thousand workers in North America were exposed to 0.03 robots and this only gradually increased to 1.2 in 2015. Hence, even though North America has a large stock of industrial robots, its robot density is relatively low. All countries, except Japan and the United Kingdom, show a tendency to increase the adoption of industrial robots. In the case of Japan, the exceptionally high-levels of robot-density have been on decline since the late 1990s. The United Kingdom has shown the overall least interest in the adoption of industrial robots. This can be observed from an almost flat robot-density plot, which is close to zero at all times.

5.2.2 Industrial robots by industries

Figure 5.3 displays the total stock of industrial robots over time for specific industries. For this we have added the total robot stock of each country in our dataset. Note that, in order to clearly display the differences between sectors, we have aggregated the original industries in our dataset. The complete details of this will be omitted since it is not important for the rest of the analysis. However, the aggregation method used is fairly straightforward. For instance, the Automotive sector in figure 5.3 refers to the sum of industries 29 Motor vehicles, trailers and semi-trailers and 30 Other transport equipment.

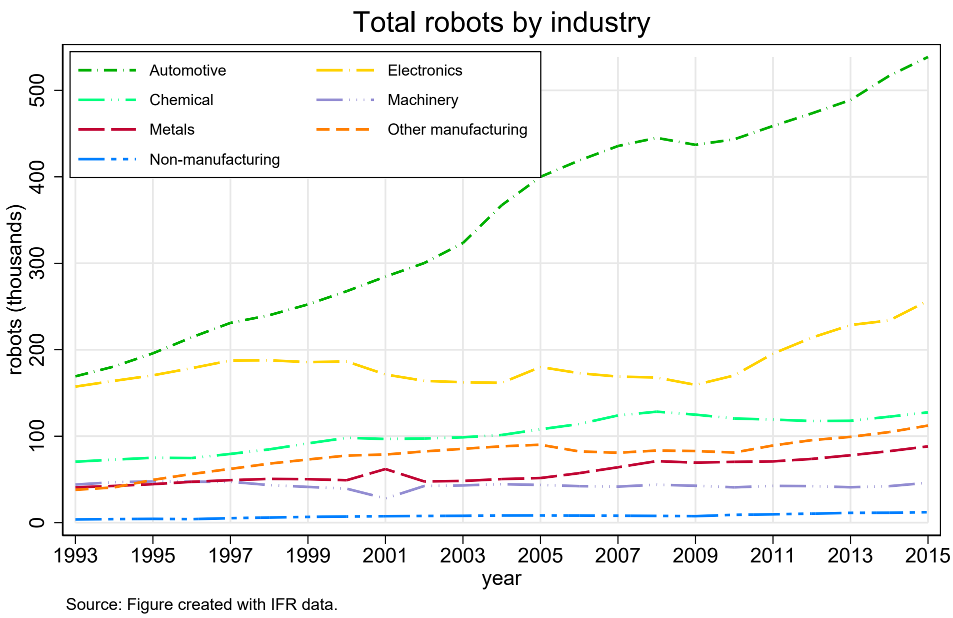

Figure 5.3: Robots by industry

We see that the automotive sector is by far the greatest installer of industrial robots followed by the electronics and chemical industries. The fact that the use of industrial robots is most prevalent in the automotive sector offers an explanation why Germany and Japan, in our between-country comparison, have historically showed such high-levels of robot-density. A similar explanation, although less obvious, holds for Korea and the electronics industry. As expected, the industry with the least investment in industrial robots is the non-manufacturing sector, which includes agriculture, mining and services.

5.2.3 Imports and offshoring

Figure 5.4 displays the total imports over time, calculated over all industries combined and for the same selection of countries as figures 5.1 and 5.2. Not surprisingly, the largest "country", North America, imports the most intermediate inputs from abroad. Similarly, the smallest country imports the least in absolute terms. Hence, using total imports as a measure for a between-country comparison is not very illuminating. To improve the comparison we need to take country-size into consideration. This is achieved by the offshoring index, which is the ratio of imported intermediates over total intermediates. Figure 5.5 displays the offshoring index over time, again calculated over all industries and the now well known selection of countries.

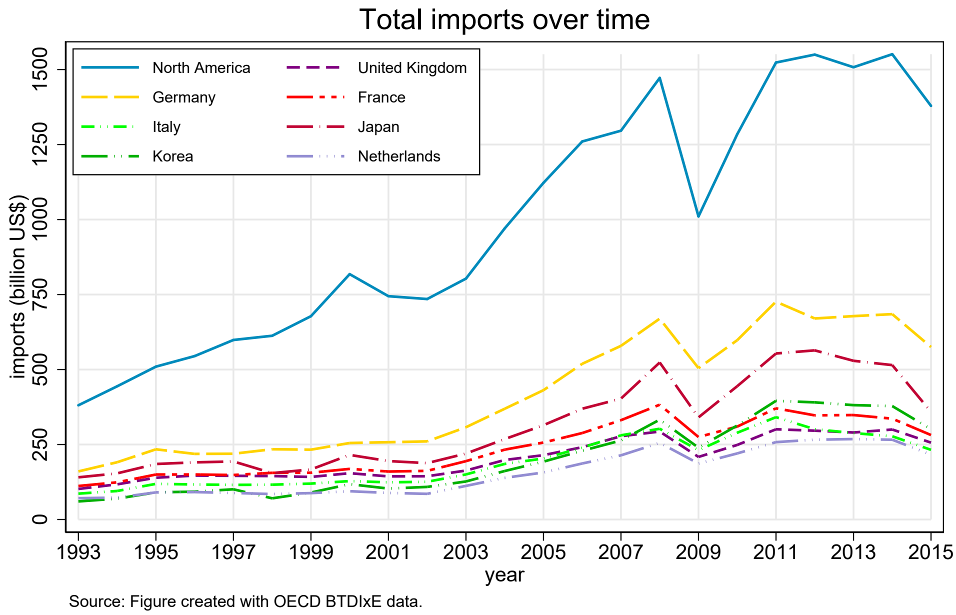

Figure 5.4: Imports

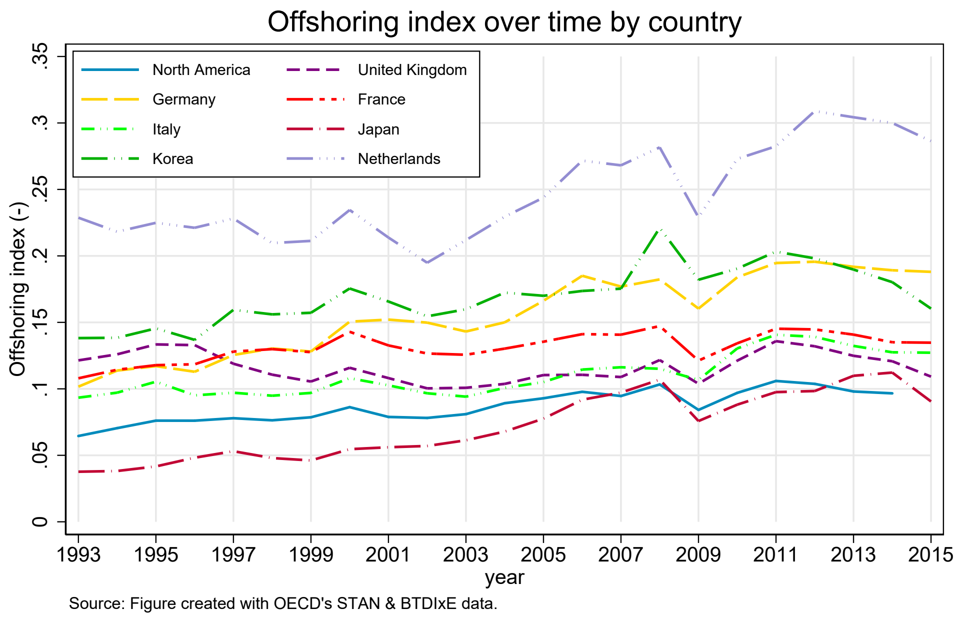

Figure 5.5: Offshoring index

Timmer et al. (2016) states that the important factors determining import intensity of final demand are:
- Per capita GDP: Richer countries usually spend a greater share of income on services, that in general are less trade intensive.
- Country size: Compared to larger countries, smaller countries typically have less variety in the supply of domestic products and therefore import more intermediates.

The relationship between country size and import intensity (i.e. the offshoring index) can clearly be observed in the above figure. The Netherlands, the smallest country included in the figure, indeed has the highest offshoring index. Bigger countries, like Japan and North America, relatively import much less intermediate inputs from abroad.
Inspecting the time period between 1993-2015, we observe that offshoring activity, both in terms of total imports and the offshoring index, increased for most countries included in the analysis. We also observe that during the Great Recession of 2008, offshoring activity in all countries dropped. However, it quickly recovered and even increased at a higher pace compared to the period before the crises. However, since 2011, the offshoring growth rate is observed to be either negative or close to zero for most countries. Here, we indeed observe the phenomenon that was described previously as the slowdown of world trade. Possibly this could be a sign that reshoring is indeed more often taking place and a phenomenon of the future.

6. Results

6.1 Data analysis

6.1.1 Fixed-effects

The following section presents the results of the regression analysis using fixed-effects. Table 6.1 depicts the coefficient estimates obtained from seven different models. These models only differ in terms of the control variables that are accounted for. The functional form of the variables and the estimation method itself are the same for each model.

Dependent variable:	**log(1 + offshore)**						
	(1) Simple	(2) Add labor intensity (interaction term)	(3) Add labor intensity (predictor)	(4) Add wage	(5) Add year-dummies	(6) Add country-trends	(7) Add industry-trends
log(1 + roboden)	0.039***	0.015	0.013	-0.024	-0.053***	-0.051***	-0.029**
	(0.009)	(0.014)	(0.014)	(0.015)	(0.017)	(0.017)	(0.014)
Intercept	0.421***	0.420***	0.474***	0.232***	0.484***	-2.344	-10.344**
	(0.009)	(0.009)	(0.048)	(0.053)	(0.084)	(4.311)	(4.291)
Control variables:							
log(1 + roboden) * dummy(labi)	✘	0.040**	0.041**	0.048***	0.045**	0.048***	0.065***
	✘	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.016)
log(1 + labi)	✘	✘	-0.123	-0.086	-0.053	-0.001	0.111
	✘	✘	(0.111)	(0.108)	(0.103)	(0.101)	(0.071)
log(wage)	✘	✘	✘	0.080***	-0.019	-0.058	-0.079**
	✘	✘	✘	(0.016)	(0.032)	(0.036)	(0.032)
Year-dummies	✘	✘	✘	✘	✔	✔	✔
Country-trends	✘	✘	✘	✘	✘	✔	✔
Industry-trends	✘	✘	✘	✘	✘	✘	✔
Observations	8091	8091	8091	8091	8091	8091	8091
Number of clusters	390	390	390	390	390	390	390
R-squared	0.013	0.017	0.019	0.051	0.091	0.123	0.405
Adjusted R-squared	0.013	0.016	0.018	0.051	0.088	0.117	0.401
Adjusted R-squared *	-	-	0.003	0.046	0.080	0.110	0.393

Note:
- Significance *** p<0.01, ** p<0.05, * p<0.1.
- Robust standard errors in parentheses.
- Estimated using fixed-effects.
- Clustering at the country-industry level.

Table 6.1: Regression analysis results

<u>*R-squared*</u>

Let's start this discussion by looking at what happens to the goodness-of-fit of the models, measured by the value of R-squared and the adjusted R-squared, when additional regressors are added to the estimation model. The R-squared of the regression is the ratio of the explained sum of squares (SSE) over the total sum of squares (SST) and is interpreted as the fraction of the sample variation in the dependent variable that is explained by the independent variables. The R-squared of a regression is always valued between 0 and 1, where the extreme values of 0 and 1 represents a poor or perfect fit to the data, respectively (Wooldridge, 2017).

The fact that the value of R-squared always increases when more predictors are added to the model, also makes it a poor tool for deciding whether an explanatory variable actually belongs in the population model. For this it would be better to look at the values for the adjusted R-squared, that can go either up or down when variables are added to the model. Inspecting table 6.1, we observe that the first three regressions show extremely small values for R-squared. In these models, the respective explanatory variables only explain about 1-2% of the variation in the logarithm of the offshoring index. A low value of R-squared means that it is hard to accurately predict the outcome of interest using the estimated model. However, low values for R-squared are not uncommon in socio-economic research and the size of R-squared, by itself, does not say anything on the reliability of the estimates. However, if adding extra explanatory variables to the model results in much greater values of (adjusted) R-squared, this could be a sign that these are important predictors in the model and by omitting them, the estimates could have suffered from omitted variable bias.
The values of R-squared belonging to the final four regressions are somewhat more acceptable. When including year-dummies and time-trends to the model, the value of R-squared jumps up. When going from model (5) to model (6), the value of R-squared increases from about 5% to 9%. When also accounting for country- and industry-specific trends in the model, together the set of predictors are able to explain about 40% of the variation in the dependent variable.

The last row in table 6.1 refers to the adjusted R-squared resulting from the regression of the specific model without our main predictor: the density of industrial robots. Hence, for the first two regressions this value is not defined. However, regarding the other five regression, subtracting this value from the original value for the adjusted R-squared, can give some indication of the relative explanatory power of robot density (i.e. its relative contribution in explaining the variation in offshoring activity). Hence, we see that also for the models including many predictors, the variation in the offshoring index that is explained by the adoption of industrial robots is still very small. Looking at model (7), for instance, when adding robot density to the model the value for the adjusted R-squared only increases from 0.393 to 0.401.

In section 5.2, figures 5.2 (page 40) and 5.5 (page 42) display the robot density and the offshoring index over time among countries, respectively. From this we observe that there exist many differences among OECD countries in both the adoption of industrial robots and the intensity in which intermediate inputs are sourced from abroad. Some of these differences can be explained easily, for instance the large robot stocks belonging to Japan and Germany or the higher offshoring indexes of smaller countries like the Netherlands. However, other observations such as the almost non-existent robot stock of the United Kingdom or the mass accumulation of robots by South Korea over the past decade are less explainable. It is likely that these phenomenon are influenced by more country-specific factors, such as the preferences of people, market circumstances and the overall environment in the country. Since these factors are exogenous, a regression model with but a few predictors is unable to explain such phenomenon. We explained in section 3.3.4 that adding trend variables allows to control for some of the exogenous increases of the dependent variable that are not explained by the explanatory variables.

After including trend variables in the model, the coefficient on the stock of industrial robots also becomes statistically significant and negative (which is what we expected to find). This means that part of the influence of industrial robots on offshoring that we estimated using the first three models, was actually the results of unobserved trending factors. If trend variables are not included in the model, and the unobserved trending factors that affect the dependent variable are also correlated with the explanatory variables, a spurious relationship is what might have been estimated. This could therefore offer an explanation for the ambiguous results found using the first four models. Although not displayed in table 6.1, the regression coefficients belonging to the trend variables are also highly significant.

We will now turn our focus on the size, statistical- and economical significance of the coefficient estimates belonging to the explanatory variables. In the discussions above, we argued that it is important to account for country- and industry-trends in estimating the effects because by including these terms in the analysis, the model more closely captures the relationship between robotization and offshoring. Therefore, we will primarily focus on the estimates of model (7), and also use this model to predict the impacts of robotization on offshoring.

Robot density
Since we are primarily interested in the effects of robotization on offshoring, let's start the discussion with our main regressor: the density of industrial robots. From regression table 6.1, we notice that our estimates differ considerably across the different models. Considering that we expected to find a negative relationship, the results seem somewhat ambiguous. In the first three regressions, the effect of the stock of industrial robots on offshoring activity is positive. However, in the final four regressions, the effect is found to be negative. Only the estimates of models (1), (5), (6) and (7) are statistically significant at the $p<0.01$ level. However, it is likely that especially the estimators from the earlier models (1)-(4) have suffered from either omitted variable bias or spurious regression, since these do not account for any exogenous influences, such as shocks or trends.

The coefficient belonging to log(1 + robots) approximately represents the elasticity of the offshoring index with respect to the robot density. Hence, the percentage change in the offshoring index is approximated by the coefficient estimate times the percentage change in the density of industrial robots. Considering the results of model (7), we estimate that if the robot density grows by 10%, then offshoring activity decreases by 0.29%. This is in agreement with the results by Carbonero et al. (2018) and De Backer et al. (2018) who respectively found offshoring to decrease by 0.30% and 0.54%, due to a 10% increase in the stock of industrial robots.

Interaction term
From the regressions that included an interaction term between the robot density and labor intensity in its dummy-form, we see that the estimates of this effect are positive and statistically significant for all models, either at the $p<0.05$ or $p<0.01$ significance level. Concerning model (7), the coefficient estimate belonging to the interaction term is 0.065 and statistically significant at the $p<0.01$ level. Based on these estimates, we would argue that the association between robotization and offshoring does depend on the labor intensity of industries. For capital-intensive sectors (dum(labi) = 0) our earlier estimates would still apply. However, for labor-intensive industries we would now estimate that, a 10% increase in the density of industrial robots results in an 0.36% (= -0.29% + 0.65%) increase in offshoring activity.

The reason this term was included was mainly motivated by the studies of Carbonero et al. (2018) and De Backer et al. (2018), that we aimed to validate. Regarding this interaction term, Carbonero et al. (2018) finds no significant difference between labor- and capital-intensive sectors. De Backer et al. (2018), on the other hand, finds that the negative association between robotics investments and offshoring becomes larger as the labor intensity of industries increases. However, this effect only holds true when the analysis is focused on the period 2010-2014. They estimate that for labor intensive industries, a 10% increase in the robot stock results in an extra 0.20% decrease in offshoring. The conflicting results of these studies with ours is something that warrants further inspection. Although Carbonero et al. (2018) states that it followed De Backer et al. (2018) in including this term in the analysis, both studies explain very little regarding the computation and the specific functional form of labor intensity (besides that including the variable in dummy-form accounts for possible endogeneity issues). In section 3.3.1 we explained that multiple measures exists for computing the values of labor intensity. It is thus possible that different measures combined with different datasets, have led to different results. However, even this explanation is not very convincing considering the magnitude of the differences in results.

However, we did explain that the direction of this effect is also theoretically ambiguous. The hypotheses is that labor intensity impacts both offshoring and the adoption of industrial robots. The greater the labor intensity, the more can be saved on labor costs. One way of doing this is to increase the volume of production activities that are conducted in developing countries with lower labor costs. The other possibility is to replace “expensive” workers with “cheaper” industrial robots that are able to perform similar tasks. But as robot investment itself influences offshoring, the effect of labor-intensity can theoretically be both positive and negative.

Labor intensity
The coefficient estimate belonging to labor intensity as a predictor by itself, is statistically insignificant in each estimated model in which it was included. Using these results we would argue that the population parameter we are estimating (i.e. the size of the effect in nature) is not significantly different from zero at the 1% level. Hence, after accounting for all other variables in our model, labor intensity has no effect on offshoring by itself. This is in agreement with the results of Carbonero et al. (2018) and De Backer et al. (2018).

Wages
Again focusing on the results of model (7), the coefficient estimates belonging to the average wage is -0.079 and statistically significant at the $p<0.05$ level. We included wages as a control variable in the model, following Carbonero et al. (2018). However, although controlling for wages in the analysis, this paper does explicitly list the estimates belonging to this term. Hence, it is not possible to compare our estimates in terms of size or statistical significance with those of Carbonero et al. (2018).

In section 3.3.2, it was argued that the effect of wages on offshoring, similar to labor intensity, is theoretically somewhat ambiguous. Intuitively we would expect that a higher average wage in the domestic market incentives firms to take advantage of lower wages in developing economies. Aggregated over whole the industry, offshoring increases (or in different terms: imports of intermediate inputs increases). However, at the same time, an increase in the average wage incentivizes firms to further automate production processes. This in turn negatively impacts offshoring activity. As the sign of the regression coefficient belonging to the average wage is negative, we could argue that the latter of these effects is greater in size. However, this reasoning is not entirely sound. What firms are mainly interested in is minimizing production costs. The decisions of firms to choose for a specific location- or configuration of production, depends not only on the average wage in the domestic market but also on foreign wages and the costs associated with robotization. Concerning labor-cost, therefore, a more determining factor with respect to the decisions of firms to offshore production processes, is the relative labor-costs advantage between foreign- and domestic-markets. Now, it is true that when wages in the domestic market increase, the cost advantage of foreign markets increase when foreign wages remain constant. But when foreign wages also increase, the comparative cost advantage can move in either direction. Hence, what should have been included in the regression model is the difference between the average wage in both the domestic and foreign markets. As discussed before, time- and data-constraints did not allow us for including a measure of foreign wage levels in the analysis.

Although a high degree of multicollinearity does not lead to bias in the estimators, it does affect the size of the standard errors. Larger standard errors make it harder to find statistical significant results. Labor intensity was calculated as total labor compensation over value added, whereas, the average wage was calculated as total labor compensation over total employment. Because both regressors were computed using total labor compensation, it seems plausible that a some degree of correlation exists between these variables in the dataset. However, this is not the case considering that the correlation coefficient is only 0.26. In model (7), the variance inflation factors (VIF) of labor intensity and the average wage are 1.78 and 4.27, respectively, which are both acceptable.

6.1.2 Robustness check

To confirm our results, we can estimate the effects using a different approach. Following Graetz and Michaels (2015) we consider the growth of the relevant variables over the time period for which data is available. For each country-industry pair we compute the compound annual growth rate (CAGR) using the formula given in equation (6.1).

$$CAGR(Var) = \left(\frac{Var_n}{Var_0}\right)^{\frac{1}{n}} - 1 \qquad (6.1)$$

In this formula, n+1 is the number of years in a cluster. Like using logarithmic forms, these variables also have percentage (annual) change interpretations. Since the CAGR variables are computed using only the first and last year of data available in each cluster, we end up with a single observation for each country-industry pair (cluster). Table 6.2 gives the descriptive statistics of the compound annual growth rate of the variables.

Descriptive Statistics: Compound annual growth rate (CAGR) variables.										
Variables	**N**	**Mean**	**Standard Deviation**	**Min**	**First Quartile**	**Median**	**Third Quartile**	**Max**	**Skewness**	**Kurtosis**
CAGR(offshore)	390	0.02	0.034	-0.16	0.002	0.017	0.033	0.189	0.28	6.939
CAGR(roboden)	338	0.11	0.08	-0.142	0.062	0.116	0.155	0.517	0.522	5.478
dummy(labi)	390	0.579	0.494	0	0	1	1	1	-0.322	1.104
CAGR(labi)	390	-0.004	0.017	-0.064	-0.012	-0.004	0.003	0.118	1.248	12.075
CAGR(wage)	390	0.035	0.024	-0.053	0.021	0.031	0.043	0.127	1.023	4.999

Table 6.2: Descriptive statistics table for the compound annual growth rate of the variables

Since it does not concern a panel dataset, the model can be estimated using OLS. We use robust standard errors, clustered at the country-level. The dataset has now lost its time-dimension and its “panel” nature. Because time is not of concern anymore, we do not have to worry about adding time-trends or year-dummy variables in order to control for exogenous shocks and trends that affect our data. Unlike estimation using fixed-effects, however, this estimation method does not get rid of time-constant factors. As these time-constant factors could be important determinants in estimating the effects, we now need to control for such factors. The best way of controlling for time-constant factors that are specific to a country or industry, is to add country- and industry-dummies to the estimation model. Adding such dummy variables allows the intercept to change, depending on the specific country and industry.

The results from regressing the compound annual growth rate of the variables are given in table 6.3. From table 6.3, we observe that when we control for country- and industry-specific factors by adding dummies to the model, the goodness-of-fit (i.e. R-squared) of the estimated model becomes much better. Furthermore, by doing this the coefficients can be estimated much more precisely, which result in statistical significant results. The coefficient belonging to robot density in model (6) is -0.050 and statistically significant at the $p<0.05$ level. Hence, based on model (6), we would estimate that if the robot density increased by 10% at the industry-level, offshoring activity would decrease by 0.50%. This estimate is of the same order as the one estimated based on fixed-effects. The coefficient belonging to the interaction term between robot density and labor intensity is -0.059 and statistically significant at the $p<0.01$ level. Also this effect is similar to what we found using fixed-effects estimation, whether its in terms of size, statistical- or economical-significance. Hence, the relationship between robotization and offshoring different for labor- and capital-intensive industries. The effect of wages on offshoring is negative and statistically significant at the p<0.05 level. This is similar to the estimates in table 6.1, however, the size of the effect (i.e. the economical significance) is now much greater. In section 6.1.1, however, we already argued that including wages by itself is not very enlightening as it is but a component of the term that should have been included: the relative cost advantage. The coefficient estimate belonging to labor intensity is also, unlike before, statistically significant at the p<0.10 level.

Dependent variable:	**CAGR(offshore)**					
	(1) Simple	(2) Add labor intensity (interaction term)	(3) Add labor intensity (predictor)	(4) Add wage	(5) Add country-dummies	(6) Add industry-dummies
CAGR(roboden)	0.008	-0.022	-0.02	-0.013	-0.049**	-0.050**
	-0.041	-0.042	-0.043	-0.038	-0.022	-0.023
Intercept	0.020***	0.020***	0.020***	0.022**	0.038***	0.039***
	-0.006	-0.006	-0.006	-0.009	-0.003	-0.003
Control variables:						
CAGR(roboden) * dummy(labi)	✘	0.047**	0.048**	0.044**	0.057***	0.059***
	✘	-0.019	-0.019	-0.019	-0.018	-0.02
CAGR(labi)	✘	✘	0.085	0.09	0.185**	0.180*
	✘	✘	-0.083	-0.078	-0.086	-0.087
CAGR(wage)	✘	✘	✘	-0.074	-0.354**	-0.364**
	✘	✘	✘	-0.202	-0.156	-0.159
Country-dummies	✘	✘	✘	✘	✔	✔
Industry-dummies	✘	✘	✘	✘	✘	✔
Observations	338	338	338	338	338	338
R-squared	0	0.01	0.012	0.013	0.243	0.255
Adjusted R-squared	-0.003	0.004	0.003	0.002	0.18	0.18
Note: - Significance *** p<0.01, ** p<0.05, * p<0.1. - Robust standard errors in parentheses. - Estimated using OLS						

Table 6.3: Regression results using annual growth variables

6.1.3 Effects by industry

We will now turn to investigate how the effects of robotization on offshoring differ among industries. This can be done by comparing the coefficient estimates resulting from the regressions that only include specific industries. In these industry-specific models, we will refrain from including the interaction term of labor intensity with the robot density, the average wage and industry-trends as predictor variables. Although the coefficient estimate belonging the interaction term is statistical significant in table 6.1, we omit this term because it causes a high degree of collinearity with the robot density variable when limiting the regression to specific industries. This can be explained by noticing that, although the dummy values of labor intensity were computed separately for each country, the distribution of industries in terms of labor intensity is relatively homogeneous among countries. Hence, if for some industry we have that dummy(labi) = 1 for the majority of observations, then the interaction term becomes indistinguishable from the robot density variable itself, which causes multicollinearity to become a problem and the standard errors to increase. The reason for excluding the average wage was that on closer inspection, as discussed in section 6.1.1, this is not the correct term to be included by itself. Furthermore, since each regression is limited to a single industry, there is no point in accounting for industry-differences. Therefore, only country-trends are included in the industry-specific regressions. Tables 6.4 and 6.5 present the results of the industry-specific models. Refer to table 4.3 (page 34) for the correspondence between the id numbers and the names of the industries.

Dependent variable:	log(1 + offshore)							
Industry:	All	1	2	3	4	5	6	7
log(1 + roboden)	-0.021	-0.106**	-0.082	0.008	0.034	-0.005	-0.01	-0.014
	(0.013)	(0.041)	(0.09)	(0.005)	(0.042)	(0.008)	(0.012)	(0.028)
Intercept	-1.243	-7.269***	-44.240***	-2.352***	-4.026***	-6.416***	7.453***	12.397***
	(4.291)	(0.605)	(5.095)	(0.445)	(0.761)	(1.298)	(0.887)	(3.008)
Control variables:								
log(1 + labi)	-0.014	0.056	-0.123	-0.028	0.093**	0.042	0.061	0.641
	(0.097)	(0.041)	(0.395)	(0.044)	(0.035)	(0.110)	(0.145)	(0.557)
Year-dummies	✔	✔	✔	✔	✔	✔	✔	✔
Country-trends	✔	✔	✔	✔	✔	✔	✔	✔
Observations	8091	567	551	542	541	541	540	536
Number of clusters	390	26	26	26	26	26	26	26
R-squared	0.115	0.636	0.83	0.788	0.528	0.474	0.716	0.476
Adjusted R-squared	0.11	0.602	0.813	0.766	0.481	0.422	0.687	0.424

Note:
- Significance *** p<0.01, ** p<0.05, * p<0.1.
- Robust standard errors in parentheses.
- Estimated using fixed-effects.
- Clustering at the country-industry level.

Table 6.4: Effects by industry (First half)

Dependent variable:	log(1 + offshore)							
Industry:	8	9	10	11	12	13	14	15
log(1 + roboden)	-0.011	0.004	-0.022	0.016	-0.039*	0.041	0.001	-0.01
	(0.015)	(0.017)	(0.024)	(0.016)	(0.021)	(0.034)	(0.005)	(0.015)
Intercept	11.090***	-4.668***	6.232	5.646	-0.035	5.075	4.637***	-0.292***
	(0.752)	(1.22)	(3.659)	(3.309)	(0.657)	(4.066)	(0.305)	(0.078)
Control variables:								
log(1 + labi)	-0.012	0.091***	0.323	0.482**	0.244	-0.096	-0.017	-0.029
	(0.118)	(0.025)	(0.243)	(0.179)	(0.269)	(0.23)	(0.077)	(0.022)
Year-dummies	✔	✔	✔	✔	✔	✔	✔	✔
Country-trends	✔	✔	✔	✔	✔	✔	✔	✔
Observations	536	525	526	529	525	525	540	567
Number of clusters	26	26	26	26	26	26	26	26
R-squared	0.545	0.493	0.629	0.469	0.363	0.517	0.737	0.547
Adjusted R-squared	0.499	0.441	0.59	0.414	0.297	0.467	0.711	0.504

Note:
- Significance *** p<0.01, ** p<0.05, * p<0.1.
- Robust standard errors in parentheses.
- Estimated using fixed-effects.
- Clustering at the country-industry level.

Table 6.5: Effects by industry (Second half)

Inspecting the estimates in regression tables 6.4 and 6.5, we observe that only for industries 1 and 12 the results are statistically significant at the p<0.05 and p<0.1 level, respectively. These are the industries *Agriculture, hunting, forestry and fishing* and *Motor vehicles, trailers and semi-trailers* (Table 4.3). For all other industries, we are unable to conclude that the estimates are significantly different from zero and that an effect exist. Hence, these results do not clearly demonstrate that large differences exists among industries with respect to the relationship between robotization and offshoring. Figure 6.1 graphically displays the industry-specific regression estimates. The blue horizontal lines correspond to the estimate and the sampling error from the regression including all industries (All in table 6.4). From observing this plot, it becomes immediately clear that, by limiting the regression to specific industries, the standard errors became much larger. This subsequently lead to a poor estimation of the regression coefficients.

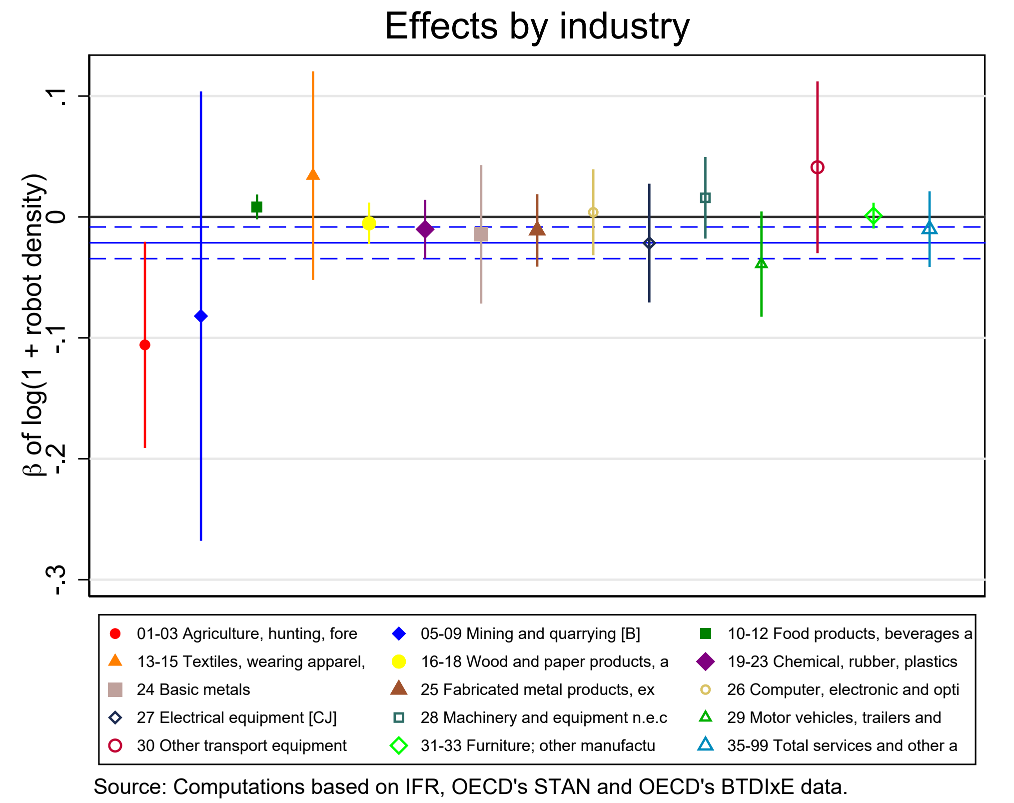

Figure 6.1: Effects by industry

It is not surprising, however, that the results became less significant for the industry-specific regressions. The statistical significance of a variable is determined by the size of its t-statistic. Since we are testing for the null hypothesis $H_0: \ \beta_j = 0$, the formula for the t-statistic for a hypothetical variable x_j is given by: $t_{\hat{\beta}_j} = \hat{\beta}_j / se(\hat{\beta}_j)$. Hence, given a specific sample, the statistical significance of a variable depends on the following two factors:

- <u>The value of the coefficient estimate</u>: If an estimator is unbiased, then its expected value is equal to the population parameter (i.e. the value of β_j in the population model). The size of the population parameter corresponds to the actual size of the effect in nature. Hence, the smaller the effect size, then the smaller the coefficient estimates and the harder it becomes to find an effect that is statistically significant.
- <u>The sampling error of the coefficient estimate</u>: The greater the sampling error, the smaller the t-statistic and the greater the probability the variable is statistically insignificant even if an effect does exist in the population (i.e. the less power). If a model is estimated using Ordinary Least Squares (OLS), then the formula for the standard error of a coefficient estimator is given by the formula given in equation (6.2).

$$se(\hat{\beta}_j) = \frac{\hat{\sigma}}{\sqrt{SST_j \cdot (1 - R_j^2)}} \qquad (6.2)$$

Hence, the following three factors are of importance in determining the size of the standard errors:

- $\hat{\sigma}$ is the root mean squared error, which is an estimator of the standard deviation of the error term σ. One way to lower the root mean squared error is to add more independent variables to the model (i.e. take some factors out of the error term).
- SST_j is the total sample variation of the explanatory variable x_j belonging to the coefficient being estimated, $\hat{\beta}_j$. The greater the sample variance of an explanatory variable, the smaller the standard error of its estimator and the more precise its coefficient can be estimated. One way to increase the sample variation in all explanatory variables is to increase the size of sample.
- $\left(1 - R_j^2\right) = 1/VIF_j$ measures the degree by which x_j is a linear relationship of the other independent variables. Or from a different perspective, R_j^2 is simply the R-squared from the regression of x_j on the other explanatory variables. If an explanatory variable is highly correlated with some of the other explanatory variables in the model, then the standard error of its estimator increases without bound. A too high degree of correlation between two or more independent variables is also called multicollinearity. The variance inflation factor (VIF), which measures the amount by which the variance of an estimator is larger due to multicollinearity, is one way to determine the severity of this problem. One way to overcome the problem of multicollinearity is to reduce the set of independent variables. However, this may in turn lead to omitted variable bias (Wooldridge, 2017).

Because we use a fixed-effects method to estimate our models and we adjusted standard errors for clustering, formula (6.2) is not entirely correct. However, this formula and especially the factors in the denominator, still give valid insights for understanding why the standard errors, and thus the statistical significance, were so different among industries.

Assuming the variables are similarly correlated in each industry's sample, the main factor that explains why the standard errors we obtained from the industry-specific regressions are so different, are the sample size and the total sample variation in robot density. When limiting the regression to specific industries, the sample size becomes much lower. This decreases the total sample variation in the density of industrial robots and helps explain why the standard errors of the coefficients found in industry-specific analysis are much larger compared to the regression which included the full dataset (the blue lines in figure 6.1). Because our panel dataset is unbalanced, the sample size also differs across industries, as seen in tables 6.4 and 6.5. However, these differences are only minor and do not by itself clarify why the standard errors are much larger for some industries. For this we have to look at the actual sample variation in robot density for particular industries. Some industries naturally have little variation in the robot stock, for instance because it is not yet possible to automate certain tasks in these industries. This is especially the case for non-manufacturing sectors like *Agriculture, hunting, forestry and fishing* and *Mining and quarrying*, which are indeed observed to have large standard errors. Other industries, like most manufacturing sectors, have much more sample variation in robot density, which results in smaller standard errors.

6.1.4 Effects by industry groups

The results of the industry-specific regressions did not elucidate matters with respect to the question whether the effects of industrial robots on offshoring are particularly strong for certain industries. From figure 6.1, we did observe that the coefficients belonging to manufacturing sectors are mostly negative and have relatively small standard errors associated with them. These are also the sectors that are currently the most robot-dense in terms of employment. One way to overcome the problem of small sample size and insignificant results is to split the total sample in two groups: high robot density industries and low robot density industries. We do this by computing the robot density for each industry in the year 2010, computed over all countries. The year 2010 is chosen as it is one of the years for which data is available on all countries. We then compare these robot densities with the median value of all industries, and group them accordingly. This should roughly divide the sample in two equal halves. The estimates obtained from limiting the analysis to these two groups of industries are presented in table 6.6. Furthermore, figure 6.2 displays these results by means of a coefficient plot.

Dependent variable:	**log(1 + offshore)**		
Industry group:	**All**	**Low**	**High**
log(1 + roboden)	-0.052***	-0.01	-0.035***
	(0.016)	(0.035)	(0.011)
Intercept	-1.65	-4.33	4.009
	(4.311)	(6.989)	(3.834)
Control variables:			
log(1 + labi)	-0.02	-0.222	0.213***
	(0.099)	(0.168)	(0.061)
Year-dummies	✔	✔	✔
Country-trends	✔	✔	✔
Observations	8091	4370	3721
Number of clusters	390	208	182
R-squared	0.12	0.165	0.19
Adjusted R-squared	0.115	0.156	0.179

Note:
- Significance *** p<0.01, ** p<0.05, * p<0.1.
- Robust standard errors in parentheses.
- Estimated using fixed-effects.
- Clustering at the country-industry level.

Table 6.6: Effects by robot-density

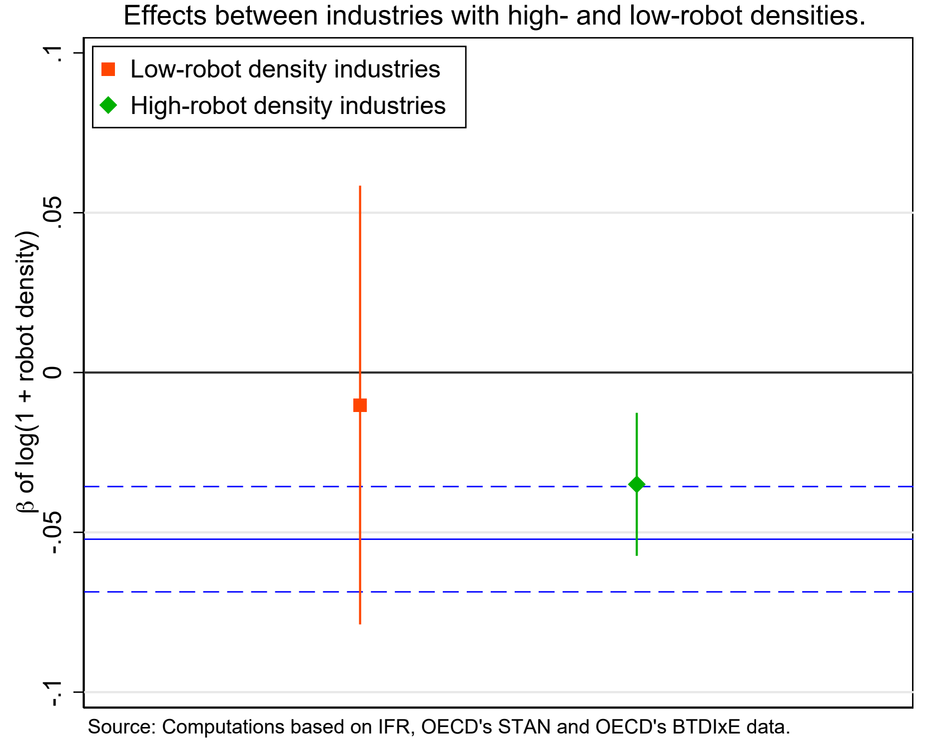

Figure 6.2: Effects by robot-density

The coefficient estimate for robot dense industries is -0.035 and statistically significant at the $p<0.01$ level. However, the estimated effect for the group of industries that on average employ less robots per worker is both statistically and economically insignificant. Since, the sample size for this group is larger, the larger sampling error must be the result of small sample variation in the robot density variable. Based on these results, we therefore estimate that if the stock of industrial robots grows by 10%, then offshoring activity of robot-dense industries decreases by 0.35%. The effect of a similar robot increase in industries that employ only a small number of robots can, based on our current data, not be estimated. The small sample variation for this group of industries, leads to a poor estimation of the coefficients.

7. Conclusion

In this analysis we have found a negative and statistically significant relationship between the adoption of industrial robots and the offshoring intensity in terms of trade in intermediate inputs. The results of this study therefore provide evidence in favor of the hypothesis that the adoption of industrial robots by OECD countries induces firms to reduce the sourcing of intermediate inputs from abroad. These results are also roughly in agreement with previous literature on this topic and with the studies we set out to check for robustness. For instance, Carbonero et al. (2018) found that a 10% increase in the robot stock leads to an impact on offshoring of about -0.30%. Furthermore, De Backer et al. (2018) estimated that, based on their most recent years of data 2010-2014, a 10% growth in robotics investment results in a -0.54% growth in offshoring activity.

However, some important differences in research design should be noted between this study and those of De Backer et al. (2018) and Carbonero et al. (2018). The first one being that the factors that were controlled for in the estimation models were somewhat different. For instance, De Backer et al. (2018) included absorptive capacity and demand as control variables, while Carbonero et al. (2018) accounted for value-added. Furthermore, both papers do not provide many details regarding the data sources used, the selection of country's and industry's included in the analysis, and the time-span of the panel dataset. Hence, these could provide explanations for the different estimates that were found.

We subsequently aimed to determine if the effect is particularly strong for certain industries. However, when the sample size decreased, the standard errors became large relative to the coefficient estimates. Therefore, in limiting the regressions to specific industries, the estimators became less precise. These results of this approach were therefore not convincing by itself and made us unable to draw conclusions with respect to industry-specific effects. However, when grouping industries with respect to their robot-density levels, it was found that the effect between robot density and offshoring particularly holds true for industries with already high levels of robot-density. One possible explanation for this is that the current capabilities of robots are particularly applicable to specific tasks which are more prevalent in certain industries. Future developments, however, could increase the variety of tasks that can be automated. For instance, Brynjolfsson and McAfee, (2014) state that artificial intelligence will increasingly become able to automate non-mechanical tasks.

Even though the conclusion is that robot adoption does affect offshoring, we have thus far not discussed the actual size of this effect in economical- or practical-terms. Using the results from our first analysis given in table 6.1, we estimated that when the number of robots per worker increases by 10%, then offshoring, measured by trade in intermediate inputs, increases by 0.29%. From my own perspective, the economical size of this impact seems relatively small. If we take the ratio of these two percentage changes, we find that they differ by a factor greater than 30. However, since these concern percentage changes, we need to put these into perspective before comparing them. In the literature, it is often stated that the diffusion of industrial robots is still in its infant stages. If the current stock of industrial robots is indeed relatively small compared to the levels of world trade, then a current change of 10% in the density of industrial robots might not be all that great in absolute terms. However, a change of 0.29% in the offshoring index could possibly be considered large when converted into comparable terms. However, since both variables are measured in different units in our data, these can not be straightforwardly compared.

Computed over all countries and industries in our dataset the density of industrial robots increased by 64% between 2005 and 2015. Holding all other factors fixed, we would estimate that over this same time-period offshoring would decrease by 1.87%. In reality, however, offshoring increased by 23% between 2005 and 2015 in our dataset. Although on aggregate offshoring increased between 2005 and 2015, this is not to say that there is nothing to worry about. For instance, the slowdown of world trade is only observed after 2011. Even though robotization does decrease offshoring, there are various other factors at play that were held fixed in the prediction. Furthermore, it is no surprise that the change in robot density only explains but a small part in the change in offshoring. In section 6.1.1, we already saw this when discussing the relative contribution of robot density in explaining the variance of the offshoring index (i.e. R-squared of the model).

In the literature review, we identified several variables that were theorized to impact either offshoring activity or the adoption of industrial robots. These include but are not limited to: demand for services, demand for customization features, labor costs in developing countries (e.g. China and India), the costs associated with industrial robots, protectionism and trade barriers. When discussing the drawbacks of our research design in section 3.7, we stated that due to issues related to the complexity of the research approach and the time-constraints of the thesis duration, we were unable to account for such factors. However, if these variables indeed have a significant impact on the dependent variable, then not controlling for these factors in the estimation model might have caused the estimators of the regression coefficients to suffer from omitted variable bias. Let's say we have a regression model and we omit an explanatory variable, that does have a non-zero coefficient, then if this variable is correlated with some other explanatory variables, all the estimators could potentially be biased (Wooldridge, 2017). Biased estimators are estimators for which the expected value is different from the actual population value that we are trying to estimate and can therefore pose a serious threat to the validity of the research design. By having included year-dummies and time-trends in the estimation model, we likely controlled for some of these confounding factors. However, biased estimators due to omitted variables can not be rules out. One possible area for future research is therefore to improve the model by controlling for more contaminating factors.

Furthermore, in the literature one often encounters contradicting theories on how certain variables are related and what the best way is to model them. Currently, most scientific research on the effects of industrial robots focus on labor markets outcomes within an economy (i.e. the same economy that adopts the industrial robots). In this area of research, a theoretical framework is developed by (Acemoglu & Restrepo, 2017). However, in the case of research of the effects on offshoring, that more concerned with the global economy and particularly with between-country effects, such a clear theoretical framework is lacking. Hence, another possible area for future research is to develop a clear and comprehensive theoretical framework that can guide and improve the formulation of estimation models.

8. Discussion

8.1 Predicted- versus actual effects

In this thesis we focused primarily on industrial robots, but these are but a part of a broader phenomenon that is often called the digitalization of manufacturing. Examples of other technologies in this category are: computer automated applications, virtual assistants, pattern recognition software and 3D printing. Our data, however, did not include these other technologies. In the literature, the stock of industrial robots is often used as a proxy for broader technological change and automation that is taking place around us. This is a valid approach as long as robotization correlates with these other technological developments. However, if this is not the case, the effects of robots could have been underestimated.

Furthermore, there exist a major drawback with data provided by IFR (2018). Namely, the stock of industrial robots is simply given in units of robots (i.e. in numbers). Hence, it only list the number of robots in each industry but does not provide info on the size, quality or performance of these robots. However, recent and future robots almost certainly have better performance than those installed in the past. As the data does not take this into account, the actual effects of robots might not have been measured correctly. One could overcome this problem by adding some measure for the average performance of robots to the estimation model. However, this data is currently not yet available.

Currently, it might be too premature to observe the actual future effects of industrial robots. In previous literature it is often claimed that the adoption of industrial robots is still in its infant stages but that this is expected to change in the near future, as technological development at the same time increases the capabilities and lowers the cost of industrial robots. This in turn increases the attractiveness for investment in robotics. A better way of explaining this is using S-curves. Both the performance and the diffusion of a technology are often described in terms of such an S-curve. For performance this means that if it is plotted against the amount of effort and money invested in its development, it initially shows slow improvement, then accelerated improvement and finally diminishing improvement (Schilling, 2016). In terms of diffusion, the adoption of a technology is also initially slow since the market is yet unfamiliar with it. However, when the technology becomes better understood and utilized, the adoption accelerates until the market becomes saturated (Schilling, 2016). If the development and diffusion of industrial robots are indeed still in their early days and if these do follow an S-curve, we can expect a period of accelerated improvement and adoption of industrial robots in the near future when the returns-to-investment and market awareness are more beneficial. When the diffusion of industrial robots starts to accelerate, its impacts will also be felt more strongly. Hence, it is possible that current available data is unable to accurately estimate the future effects of industrial robots on the location of production and the international trade in intermediate inputs.

Furthermore, as both the robot stock and the offshoring index appear in logarithmic-form in our models, we are basically estimating a constant elasticity model that imposes a constant percentage effect of robots on offshoring. However, this model was chosen by us for estimating the effects and are not a law of nature. It is perfectly possible that in the future, the impacts in terms of percentage changes either increases or decreases.

Although most of the literature agrees that robotization will become increasingly common in the future. Some disagreement exist and these counter arguments should be given attention too. Naudé (2019) thinks that the impact on job losses, inequality and productivity have been overestimated and that a “robocalypse”, leading to mass unemployment and spiraling inequality, is likely not going to happen. He supports this claim by pointing to the fact that many empirical studies did not find any significant effect. Furthermore, the predictions that seem most alarming are those of forward-looking studies that calculate the possibility of certain tasks being automated in the near future, including Frey and Osborne (2013). However, these are based on certain assumptions about the direction of technological development. If different assumptions are used, the predictions become less severe (Naudé, 2019). Research could therefore have been influenced by the high expectations concerning technologies such as robotics and AI. However, it is possible that these turn out into an anti-climax if future research and development becomes subject to decreasing returns-to-investment or get increasingly complex.

8.2 Policy- and ethical-issues

8.2.1 Promoting automation

Global trade and economic integration have contributed to growth and prosperity worldwide and provided benefits to both emerging- and advanced- economies alike. Those for emerging economies included, for instance, higher-income levels, less poverty and better access to goods and services (Dao et al., 2017). Developed countries, on the other hand, benefited through productivity gains, access to critical resources and lower-prices. However, in the case of automation, the distribution of benefits between developed- and developing-countries are less reciprocal. Until now, the upward trend in automation has become especially widespread throughout the developed world. Developing countries, on the other hand, have not yet started to robotize within their own boundaries extensively. However, because of their involvement in GVCs and the fact that their strong export position is largely based on low labor costs, these countries are not immune to experience impacts due to robotization elsewhere.

The rapid growth of GVCs over the past decade was primarily the result of an upward trend in offshoring activity and the international sourcing of intermediates. Previously, the main motivating factor for firms to relocate production activities towards emerging markets were lower labor costs. However, current developments are changing the cost-benefit analysis with regards to the location of production. First, the prices of industrial robots are declining while at the same time their performance is improving. This in turn, increases the amount of tasks for which robots are becoming a viable method of production. Most of the production processes that were previously offshored consisted of routine and labor-intensive tasks. However, these same characteristics are also considered most suitable for automation (Dao et al., 2017). Hence, the increasing capabilities and falling prices of robots act to lower the labor cost advantage of developing countries. Making matters worse is the fact that labor cost have been rising in a number of emerging economies. Hence, in terms of production cost, foreign employment and industrial robots are directly in competition with each other. While the need for firms to relocate production processes to foreign markets is eroding, the importance of GVCs is decreasing. This could possibly offer an explanation for the slowdown of world trade that has been documented by Timmer et al. (2016).

It is sometimes stated that robots will bring about a renaissance of manufacturing in OECD economies. This is because of two reasons: (1) the potential of robots to achieve higher productivity and (2) robots make manufacturing in the developed world more attractive. Kinkel et al. (2015), for instance, states that industrial robots are a key enabler for maintaining and increasing labor productivity in European companies and to strengthen their international competitiveness in terms of cost-structures. Governments are also increasingly recognizing industrial robots to be a key economic driver. Hence, besides policies that deal with the negative consequences of automation, there is a growing number of policy proposals that promote for an acceleration of the diffusion and development of automation technologies. Within the European Union, for instance, it is argued that in order to better exploit the full potential of industrial robots, the barriers to investment should be lowered for especially small and medium-sized enterprises (SME). This could be achieved through stimulating new business models on the supply-side of robotics or by promoting the development of cost-friendly robot solutions, such as modular robots.

However, because automation could lead to the re-shoring of manufacturing jobs from emerging economies, promoting for a wider diffusion of automation in the developed world inadvertently affects the developing world. Such policies could therefore oppose or obstruct the further development and structural change of developing countries and may exacerbate the process of premature de-industrialisation, which according to Rodrik (2015), could cause social instability and conflict. Hence, from an ethical standpoint it could be immoral to promote for further robotization in the developed world. In absolute terms, developing countries have benefited the most from globalization and thus have a responsibility to assist in the further development and industrialization of the developing world. Hence, the question that should still be asked is: What should be the role of governments, companies, international organizations and other institutions in the developed world in order to help reduce the negative impacts of automation on developing countries?

8.2.2 Universal Basic Income

As discussed in section 2.4, research findings expect that the installment of industrial robots and automation will pose several threats to labor markets. Most notably, these unintended and potentially disruptive consequences include: declining real wages, income inequality and unemployment. However, in terms of productivity and GDP, economies could greatly benefit from these technologies. In section 2.7, we discussed several policies that were proposed as a way to overcome the negative consequences of automation on the economy. One policy that since recently came under particular public attention is UBI. As discussed in section 2.7, UBI unconditionally provides each citizen with an amount of money on a regular basis, in order to cover their basic expenses and provide them with a decent standard of living.

In response to the rapid development of robotization and AI, several prominent tech executives are advocating for some type of UBI policy to cope with potential disruptive effects of technology on society. These include Elon Musk (CEO of Tesla), Mark Zuckerberg (CEO of Facebook) and Bill Gates (Founder of Microsoft). However, politicians are generally more skeptic towards the effects of technology on labor markets. For instance, according to Treasury Secretary Steven Mnuchin, it will still take around 50 to a 100 years from now until the impacts of automation become a more pressing subject (White, 2017). This confirms that, the belief that technology overall complements rather than substitutes human labor is still widespread in public opinion. Recognizing that many politicians are clueless regarding the upcoming industrial transformation, Andrew Yang, a 2020 Democratic presidential candidate, made automation and the regulation of AI to be the central issues of his campaign. To guarantee that everyone benefits from the shift in automation that is happening around us, he advocates for a type of UBI called the "Freedom Dividend", which provides an unconditional income to every citizen. Furthermore, similarly to what was discussed in section 2.7, he proposes the establishment of a governmental department of technology, consisting of technological experts with the role of advising policy makers regarding issues related to automation and AI (Winick, 2018).

Until now, research on how UBI affects the psychology and mood of people has been very limited. The proponents and opponents of such policies have different opinions on this. Supporters of UBI, like Andrew Yang, often argue in favor of UBI from the perspective of freedom or leisure rather than income. The notion of freedom is central to most democracies and Western civilizations, in which it most often means that each person is free to do as one pleases without unjust constraints. However, formal freedom is different from freedom in real effective terms. When people lose their jobs, most of their time will be spent simply on the struggle to survive and the search for some source of income. This restricts them in their ability to exercise their rights of freedom. What UBI intends to do is to redistribute "freedom" from the wealthy to the working class and to ensure that people have equal opportunity to achieve their goals and desires. Proponents thus state that when everyone is provided with a basic income, people are freed both from routine work, which is dreadful and boring, and the struggle to survive. This allows them to spent more time on the things they love and to embark on more creative and meaningful projects or experiment with different economic arrangements. Generally, and specifically in business literature, higher motivation implies greater productivity and stimulates entrepreneurship. It is thus possible that UBI results in an extra positive effect on the economy. Critics of UBI, however, call it "handing out unearned money", which they claim will disincentive people from working and deprive them from having a purpose in life. Moreover, they often state that is it too expensive to fund a policy of this size.

Hence, much of the debate on UBI focuses on the question: “Who is going to pay for it?”. One way to gather the necessary funds, as proposed by Bill Gates, is by taxing companies based on their use of robots and other automation technologies. One way of doing this is implementing a sliding scale automation tax, which determines the corporate tax rate depending on the degree by which processes are automated versus done by human labor. As an alternative to a tax system that specifically targets robots and automation, another possibility is to increase the overall corporate tax rate. However, some economists, like Larry Summers, disagree with the proposal to tax robots and automation. He states that taxing robots discourages investment and innovation, and thus hinders the further development and installment of these technologies. As this blocks the economy to exploit the full productivity potential of automation, society can not reap all its benefits and is thus counterproductive. A more effective policy to compensate the workforce, he claims, is to subsidize education and re-training programs (Wolla, 2018). These concerns are also echoed by the European Parliament, that in 2017 rejected a proposal to tax robots because of concerns it would discourage innovation (Abbott & Bogenschneider, 2018). However, in the case of widespread automation, changes in tax policy are going to be necessary with or without UBI. Currently, in most countries capital is on aggregate taxed less heavily than labor. Such a system thus encourages companies to further automate their production activities and increase their capital-to-labor ratio. However, more capital inadvertently means less tax revenue for the government unless it adopts a more factor neutral, or even labor promoting, tax system (Abbott & Bogenschneider, 2018).

Taxing the large profits of such companies could be a valid way to finance UBI, however, there are also people that think it is morally unjust for the government to get involved in- and redistribute the profits of companies. Ultimately, however, society at large owns the resources from which robots and other forms of automation are constructed. We explained in section 2.2.1 that ever since the digital economy became a thing, firms that automated the most have also made the greatest gains in terms of productivity and market share. As the saying goes “one man’s loss is another man’s gain”, these companies profit the most from automation but also cause the greatest job-losses for the rest of society. Furthermore, many current technological advances, including AI, directly derive their value from exploiting the personal data of everyday people. Hence, from this perspective, taxing companies to share the profits made through automation, and making them responsible for the displacement and unemployment of workers, can be morally justifiable.

Furthermore, a redistribution of income could also benefit companies themselves. Economic growth, by the workings of capitalism, materializes through increasing consumption levels of goods and services. However, in order to consume, consumerist need income. By traditional economic theory, when the economy grows and labor becomes more productive, wages rise as a result. This in turn leads to more consumption and thus further economic growth. However, when it becomes possible for robots to substitute labor, it either causes unemployment or puts downward pressure on the wages of the affected workers. In both of these cases the income of consumerist declines which leads to less consumption. Hence, in the case of widespread automation and large scale joblessness, UBI allows for a basic level of income and consumption to continue.

Automation has potential to boost economic growth, through improvements in efficiency and productivity. If widespread automation indeed becomes reality, it will generate more wealth than ever before. This could benefit society at large, as long as the benefits are distributed fairly. However, without policy intervention this wealth will only accrue to the owners of capital, which leads to greater social inequality and exacerbates existing problems on the labor market. The main issue in the design of policies such as UBI and tax systems to fund it, is to find the solution that does not hinder investment and innovation as much as possible, but at the same time redistributes the benefits in the most fair way. Hence, automation poses several questions for future public policy. Although, at present, there still exists a lot of skepticism towards the potential disruptive effects caused by automation trends, if the concerns on the labor market do turn out to be true and socio-economic effects start to take shape, then widespread acceptance for measures such as UBI will result from economic urgency.

8.2.3 Global policies

Although automation is expected to disrupt both the developed- and developing world, multiple studies predict that workers in emerging economies are at greater risk of becoming negatively affected by the proliferation of automation. Several reasons for this exist, as discussed in section 2.6.5. First, employment in developing countries is characterized by a high degree of routine and labor-intensive work, which is most susceptible to automation. Secondly, the bargaining power of labor in developing countries is much lower due to it having limited labor market institutions and the prevalence of informal employment. Third, adequate educational systems are often lacking, which limit the possibilities for retraining and acquiring the necessary skills for new jobs and those that are less prone to becoming automated. Moreover, due to their dependence on GVCs, developing countries are primarily affected by automation trends in the developed world. Hence, if the extra profits permitted by automation are not shared across borders, developing countries also do not benefit through increases in productivity. Furthermore, protectionist trade policies, such as the tariffs imposed by President Trump to protect the US economy from foreign imports, could accelerate the trend in reshoring and the slowdown of world trade, which will further threaten the economies in the developing world.

Currently, most developing countries do not have the jurisdiction or the funds in place to put a policy like UBI into action. Furthermore, most policy proposals that deal with automation's disruptive effects, such as UBI and other ones discussed in section 2.7, are designed to tackle inequality and unemployment within a specific country. These will thus leave the citizens of developing countries out of consideration. However, if automation does indeed cause greater disruption to developing countries the question that should again be asked is, who is responsible for this? In section 8.2.2, we made the argument that companies automating their workforces are in part responsible for the disruptive effects on the labor market. However, the companies that are the greatest investors in automation are predominantly MNEs (Autor et al., 2017). Because these companies operate around the globe and furthermore exploit the resources of developing countries, the same argument can be made with respect to the responsibility question concerning the impacts in developing countries.

Hence, to aid developing countries in managing disruptive effects related to technology and help them transition into a more developed economy and society, global collective action is necessary. One possibility is to introduce a type of UBI policy that covers the entire world. However, developing and implementing a policy dealing with technological unemployment and inequality on a global scale is even much harder to realize. Inevitably, collaboration is needed between multiple governments, international organizations, MNEs and other institutions, which likely takes an extended amount of time to develop. However, countries working together on a global level also has other benefits. Many countries engage in tax competition in order to attract foreign capital investment, which partly explains why capital is in most countries taxed less heavily than labor. Hence, global policy directed at automation can also prevent that companies simply shift their capital into other cheaper markets when confronted with domestic robot taxes. Furthermore, reshoring can be discouraged by imposing penalties or higher taxes on the companies that do.

In the short-term, therefore, a better possibility might be to provide extra international aid to assist countries with adjusting to automation. For instance, by investment in training-programs or improving the eduction system in developing countries, so that workers can learn the skills needed for higher-level jobs that are less threatened by automation. Another possibility is to establish some type of international organization that oversees the impacts of automation in developing countries and that promotes their further economic development and structural transformation. By collaborating with governments of developing countries it might be possible to improve the social security and safety nets of workers in order to better protect them against automation. However, additional research is needed for understanding what the best solutions are and how automation affects the development of different developing countries.

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A. Appendix
A.1 Classification of industries

Industry classification		
ISIC4 (STAN)	**BTDIxE**	**IFR**
01-99 Total	DTOTAL - TOTAL	000-All Industries
01-03 Agriculture, hunting, forestry and fishing [A]	D01T03 - Agriculture, forestry and fishing [A]	A-B-Agriculture, forestry, fishing
05-09 Mining and quarrying [B]	D05T08 - Mining and quarrying [B]	C-Mining and quarrying
10-33 Manufacturing [C]	D10T32 - Manufacturing [C]	D-Manufacturing
10-12 Food products, beverages and tobacco [CA]	D10T12 - Food products, beverages and tobacco [CA]	10-12-Food and beverages
13-15 Textiles, wearing apparel, leather and related products [CB]	D13T15 - Textiles, wearing apparel, leather and related products [CB]	13-15-Textiles
16-18 Wood and paper products, and printing [CC]	D16T18 - Wood, paper products and printing [CC]	16-Wood and furniture + 17-18-Paper
19-23 Chemical, rubber, plastics, fuel products and other non-metallic mineral products	D19T22 - Chemicals, rubber, plastics and fuel products + D23 - Other non-metallic mineral products	19-22-Plastic and chemical products + 23-Glass, ceramics, stone, mineral products (non-auto
24 Basic metals	D24 - Basic metals	24-Basic metals
25 Fabricated metal products, except machinery and equipment	D25 - Fabricated metal products, except machinery and equipment	25-Metal products (non-automotive)
26 Computer, electronic and optical products [CI]	D26 - Computer, electronic and optical products [CI]	260-Electronic components/devices + 261-Semiconductors, LCD, LED + 262-Computers and peripheral equipment + 263-Info communication equipment, domestic and prof. (+ 265-Medical, precision, optical instruments
27 Electrical equipment [CJ]	D27 - Electrical equipment [CJ]	271-Electrical machinery n.e.c. (non-automotive) + 275-Household/domestic appliances + 279-Electrical/electronics unspecified
28 Machinery and equipment n.e.c. [CK]	D28 - Machinery and equipment n.e.c. [CK]	28-Industrial machinery + 289-Metal, unspecified
29 Motor vehicles, trailers and semi-trailers	D29 - Motor vehicles, trailers and semi-trailers	29-Automotive
30 Other transport equipment	D30 - Other transport equipment	30-Other vehicles
31-33 Furniture; other manufacturing; repair and installation of machinery and equipment [CM]	D31T32 - Furniture, other manufacturing [CM]	91-All other manufacturing branches
35-39 Electricity, gas and water supply; sewerage, waste management and remediation activities [D-E] + 41-43 Construction [F] + 45-99 Total services [G-U]	D35 - Electricity, gas, steam and air conditioning supply [D] + D37T39 - Waste collection, treatment and disposal activities; materials recovery + D36T99 - Other activities	E-Electricity, gas, water supply + F-Construction + P-Education/research/ development + 90-All other non-manufacturing branches

Table A.1: Correspondences between industry-classifications

A.2 Descriptive statistics tables

01-03 Agriculture, hunting, forestry and fishing [A]										
Variables	**N**	**Mean**	**Standard Deviation**	**Min**	**First Quartile**	**Median**	**Third Quartile**	**Max**	**Skewness**	**Kurtosis**
offshore	567	0.217	0.157	0.015	0.099	0.175	0.299	0.924	1.528	6.289
roboden	567	0.082	0.209	0	0.001	0.013	0.066	1.657	4.735	28.325
labi	567	0.252	0.099	0.072	0.191	0.241	0.292	0.608	0.84	3.917
wage	567	7.764	6.054	0.446	2.797	6.42	11.04	26.636	1.005	3.437
log(1+offshore)	567	0.189	0.12	0.015	0.094	0.161	0.261	0.654	1.072	4.43
log(1+roboden)	567	0.066	0.143	0	0.001	0.013	0.064	0.977	3.837	19.541
dummy(labi)	567	0.041	0.197	0	0	0	0	1	4.658	22.694
log(1+labi)	567	0.222	0.077	0.069	0.175	0.216	0.256	0.475	0.592	3.451
log(wage)	567	1.68	0.947	-0.808	1.029	1.859	2.402	3.282	-0.509	2.453

Table A.2: Descriptive statistics for Agriculture, hunting, forestry and fishing

05-09 Mining and quarrying [B]										
Variables	**N**	**Mean**	**Standard Deviation**	**Min**	**First Quartile**	**Median**	**Third Quartile**	**Max**	**Skewness**	**Kurtosis**
offshore	551	11.48	17.183	0.056	2.105	5.469	11.955	119.374	2.946	12.944
roboden	551	0.93	2.961	0	0	0.038	0.37	32.997	6.187	52.36
labi	551	0.406	0.235	0.035	0.202	0.413	0.538	1.386	0.834	4.438
wage	551	50.915	34.933	2.014	25.677	45.827	67.045	200.41	1.303	5.137
log(1+offshore)	551	1.925	1.049	0.055	1.133	1.867	2.561	4.791	0.425	2.693
log(1+roboden)	551	0.328	0.619	0	0	0.038	0.315	3.526	2.499	9.16
dummy(labi)	551	0.187	0.39	0	0	0	0	1	1.606	3.579
log(1+labi)	551	0.327	0.162	0.034	0.184	0.346	0.431	0.87	0.298	3.006
log(wage)	551	3.663	0.809	0.7	3.246	3.825	4.205	5.3	-0.838	3.69

Table A.3: Descriptive statistics for Mining and quarrying

10-12 Food products, beverages and tobacco [CA]										
Variables	N	Mean	Standard Deviation	Min	First Quartile	Median	Third Quartile	Max	Skewness	Kurtosis
offshore	542	0.085	0.049	0.017	0.052	0.073	0.105	0.287	1.256	4.587
roboden	542	3.281	5.62	0	0.258	1.144	3.382	39.105	3.405	17.413
labi	542	0.527	0.105	0.235	0.451	0.516	0.599	0.91	0.174	2.904
wage	542	31.563	17.556	2.512	16.902	30.62	41.623	81.36	0.463	2.612
log(1+offshore)	542	0.08	0.044	0.017	0.051	0.07	0.1	0.252	1.129	4.162
log(1+roboden)	542	0.98	0.885	0	0.23	0.763	1.477	3.691	0.87	2.97
dummy(labi)	542	0.476	0.5	0	0	0	1	1	0.096	1.009
log(1+labi)	542	0.421	0.069	0.211	0.372	0.416	0.469	0.647	-0.023	2.942
log(wage)	542	3.248	0.716	0.921	2.827	3.422	3.729	4.399	-0.971	3.536

Table A.4: Descriptive statistics for Food products, beverages and tobacco

13-15 Textiles, wearing apparel, leather and related prodcuts [CB]										
Variables	N	Mean	Standard Deviation	Min	First Quartile	Median	Third Quartile	Max	Skewness	Kurtosis
offshore	541	0.49	0.296	0.042	0.254	0.437	0.66	1.546	0.913	3.812
roboden	541	0.72	2.721	0	0.004	0.095	0.432	27.199	6.791	53.545
labi	541	0.688	0.184	0.456	0.62	0.672	0.725	4.236	13.397	255.574
wage	541	23.835	14.029	1.827	12.529	23.057	31.514	65.416	0.494	2.68
log(1+offshore)	541	0.38	0.19	0.041	0.226	0.363	0.507	0.935	0.42	2.772
log(1+roboden)	541	0.281	0.511	0	0.004	0.091	0.359	3.339	3.465	17
dummy(labi)	541	0.941	0.236	0	1	1	1	1	-3.738	14.969
log(1+labi)	541	0.52	0.077	0.376	0.482	0.514	0.545	1.656	6.256	89.099
log(wage)	541	2.935	0.775	0.603	2.528	3.138	3.45	4.181	-0.931	3.198

Table A.5: Descriptive statistics for Textiles, wearing apparel, leather and related products

16-18 Wood and paper products, and printing [CC]										
Variables	N	Mean	Standard Deviation	Min	First Quartile	Median	Third Quartile	Max	Skewness	Kurtosis
offshore	541	0.404	0.228	0.047	0.239	0.351	0.544	0.991	0.583	2.448
roboden	541	1.474	2.69	0	0.056	0.553	1.61	18.418	3.708	19.303
labi	541	0.587	0.109	0.298	0.506	0.598	0.664	0.895	-0.162	2.532
wage	541	32.019	18.29	1.598	14.912	33.087	44.968	80.594	0.215	2.224
log(1+offshore)	541	0.326	0.158	0.046	0.214	0.301	0.435	0.689	0.32	2.217
log(1+roboden)	541	0.619	0.662	0	0.055	0.44	0.959	2.966	1.276	4.259
dummy(labi)	541	0.76	0.428	0	1	1	1	1	-1.216	2.478
log(1+labi)	541	0.459	0.07	0.261	0.409	0.469	0.509	0.639	-0.318	2.589
log(wage)	541	3.225	0.797	0.469	2.702	3.499	3.806	4.389	-1.028	3.358

Table A.6: Descriptive statistics for Wood and paper products, and printing

19-23 Chemical, rubber, plastics, fuel products and other non-metallic mineral products										
Variables	**N**	**Mean**	**Standard Deviation**	**Min**	**First Quartile**	**Median**	**Third Quartile**	**Max**	**Skewness**	**Kurtosis**
offshore	540	0.483	0.198	0.07	0.359	0.468	0.594	1.135	0.416	3.154
roboden	540	8.064	9.874	0	1.742	4.679	10.314	68.822	2.864	14.861
labi	540	0.447	0.102	0.094	0.377	0.464	0.522	0.65	-0.797	3.727
wage	540	43.913	25.063	3.581	23.332	40.911	60.61	111.428	0.472	2.57
log(1+offshore)	540	0.385	0.132	0.068	0.307	0.384	0.466	0.758	0.031	2.933
log(1+roboden)	540	1.749	0.964	0	1.009	1.737	2.426	4.246	0.078	2.357
dummy(labi)	540	0.122	0.328	0	0	0	0	1	2.307	6.321
log(1+labi)	540	0.367	0.073	0.09	0.32	0.381	0.42	0.501	-1.042	4.429
log(wage)	540	3.565	0.74	1.276	3.15	3.711	4.104	4.713	-0.953	3.409

Table A.7: Descriptive statistics for Chemical products and other non-metallic mineral products

24 Basic metals										
Variables	**N**	**Mean**	**Standard Deviation**	**Min**	**First Quartile**	**Median**	**Third Quartile**	**Max**	**Skewness**	**Kurtosis**
offshore	536	1.561	3.789	0.058	0.476	0.691	1.297	37.372	6.755	55.341
roboden	536	3.529	5.739	0	0.441	1.615	4.202	57.922	4.154	27.147
labi	536	0.6	0.166	0.23	0.478	0.591	0.696	1.312	0.53	3.446
wage	536	43.287	22.641	1.247	25.06	43.531	59.522	109.786	0.195	2.5
log(1+offshore)	536	0.68	0.538	0.056	0.39	0.525	0.832	3.647	2.753	12.713
log(1+roboden)	536	1.092	0.842	0	0.365	0.961	1.649	4.076	0.711	3.017
dummy(labi)	536	0.854	0.353	0	1	1	1	1	-2.01	5.042
log(1+labi)	536	0.465	0.102	0.207	0.391	0.464	0.528	0.838	0.223	2.968
log(wage)	536	3.564	0.744	0.221	3.221	3.773	4.086	4.699	-1.415	5.352

Table A.8: Descriptive statistics for Basic metals

25 Fabricated metal products, except machinery and equipment										
Variables	**N**	**Mean**	**Standard Deviation**	**Min**	**First Quartile**	**Median**	**Third Quartile**	**Max**	**Skewness**	**Kurtosis**
offshore	536	0.404	0.282	0.019	0.22	0.33	0.512	1.894	1.857	8.055
roboden	536	7.854	8.099	0	1.395	5.629	12.456	51.785	1.55	6.235
labi	536	0.644	0.109	0.291	0.574	0.652	0.719	1.054	-0.451	4.081
wage	536	33.921	20.892	1.852	16.491	33.253	45.158	163.815	1.282	7.298
log(1+offshore)	536	0.322	0.18	0.019	0.199	0.285	0.414	1.063	1.092	4.648
log(1+roboden)	536	1.727	1.018	0	0.874	1.891	2.599	3.966	-0.162	1.866
dummy(labi)	536	0.961	0.194	0	1	1	1	1	-4.75	23.565
log(1+labi)	536	0.495	0.068	0.256	0.454	0.502	0.542	0.72	-0.747	4.506
log(wage)	536	3.293	0.762	0.617	2.803	3.504	3.81	5.099	-0.973	3.778

Table A.9: Descriptive statistics for Fabricated metal products, except machinery and equipment

26 Computer, electronic and optical products [CI]										
Variables	**N**	**Mean**	**Standard Deviation**	**Min**	**First Quartile**	**Median**	**Third Quartile**	**Max**	**Skewness**	**Kurtosis**
offshore	525	0.881	0.682	0.066	0.546	0.746	0.956	5.755	3.342	18.339
roboden	525	7.487	17.885	0	0.385	1.926	6.207	156.808	4.698	28.786
labi	525	0.521	0.375	0.176	0.412	0.511	0.591	8.502	18.435	392.937
wage	525	46.416	26.692	2.747	26.292	44.589	65.182	116.873	0.275	2.27
log(1+offshore)	525	0.588	0.276	0.064	0.436	0.558	0.671	1.91	1.501	7.031
log(1+roboden)	525	1.29	1.128	0	0.326	1.074	1.975	5.061	0.969	3.516
dummy(labi)	525	0.282	0.45	0	0	0	1	1	0.969	1.94
log(1+labi)	525	0.409	0.121	0.162	0.345	0.413	0.464	2.251	6.651	102.967
log(wage)	525	3.588	0.824	1.01	3.269	3.797	4.177	4.761	-1.172	3.816

Table A.10: Descriptive statistics for Computer, electronic and optical products

27 Electrical equipment [CJ]										
Variables	**N**	**Mean**	**Standard Deviation**	**Min**	**First Quartile**	**Median**	**Third Quartile**	**Max**	**Skewness**	**Kurtosis**
offshore	526	0.853	0.59	0.022	0.531	0.728	1.058	3.942	1.946	8.296
roboden	526	8.77	19.012	0	0.571	3.053	7.393	153.06	4.283	23.58
labi	526	0.597	0.1	0.296	0.535	0.593	0.662	1.091	0.222	4.862
wage	526	40.36	22.982	2.094	21.491	38.458	56.963	113.141	0.428	2.753
log(1+offshore)	526	0.575	0.277	0.022	0.426	0.547	0.722	1.598	0.752	4.171
log(1+roboden)	526	1.463	1.154	0	0.452	1.399	2.127	5.037	0.702	3.12
dummy(labi)	526	0.719	0.45	0	0	1	1	1	-0.972	1.946
log(1+labi)	526	0.466	0.063	0.259	0.428	0.466	0.508	0.738	-0.107	4.363
log(wage)	526	3.472	0.766	0.739	3.068	3.65	4.042	4.729	-1.054	3.644

Table A.11: Descriptive statistics for Electrical equipment

28 Machinery and equipment n.e.c. [CK]										
Variables	**N**	**Mean**	**Standard Deviation**	**Min**	**First Quartile**	**Median**	**Third Quartile**	**Max**	**Skewness**	**Kurtosis**
offshore	529	0.648	0.578	0.018	0.318	0.526	0.763	4.016	2.572	11.559
roboden	529	4.173	4.825	0	0.605	2.556	6.409	27.801	1.806	6.717
labi	529	0.631	0.102	0.306	0.566	0.63	0.689	1.159	0.195	4.599
wage	529	41.325	22.741	2.188	22.335	40.987	57.04	114.546	0.333	2.707
log(1+offshore)	529	0.455	0.281	0.018	0.276	0.423	0.567	1.613	1.298	5.308
log(1+roboden)	529	1.258	0.884	0	0.473	1.269	2.003	3.36	0.185	1.958
dummy(labi)	529	0.79	0.408	0	1	1	1	1	-1.425	3.031
log(1+labi)	529	0.487	0.063	0.267	0.449	0.488	0.524	0.77	-0.124	4.32
log(wage)	529	3.502	0.763	0.783	3.106	3.713	4.044	4.741	-1.191	4.091

Table A.12: Descriptive statistics for Machinery and equipment n.e.c.

29 Motor vehicles, trailers and semi-trailers										
Variables	**N**	**Mean**	**Standard Deviation**	**Min**	**First Quartile**	**Median**	**Third Quartile**	**Max**	**Skewness**	**Kurtosis**
offshore	525	0.765	0.861	0.006	0.271	0.435	0.996	5.874	2.605	11.148
roboden	525	46.404	55.611	0	9.31	30.017	64.662	473.85	2.859	15.803
labi	525	0.594	0.15	0.213	0.478	0.594	0.697	1.137	0.206	2.733
wage	525	44.058	27.235	3.165	23.107	43.145	57.908	274.056	1.665	12.604
log(1+offshore)	525	0.489	0.368	0.006	0.24	0.361	0.691	1.928	1.349	4.662
log(1+roboden)	525	3.1	1.462	0	2.333	3.435	4.185	6.163	-0.649	2.55
dummy(labi)	525	0.554	0.498	0	0	1	1	1	-0.218	1.048
log(1+labi)	525	0.462	0.094	0.193	0.391	0.467	0.529	0.759	-0.023	2.59
log(wage)	525	3.553	0.768	1.152	3.14	3.765	4.059	5.613	-1.013	3.778

Table A.13: Descriptive statistics for Motor vehicles, trailers and semi-trailers

30 Other transport equipment										
Variables	**N**	**Mean**	**Standard Deviation**	**Min**	**First Quartile**	**Median**	**Third Quartile**	**Max**	**Skewness**	**Kurtosis**
offshore	525	0.717	2.376	0.027	0.216	0.442	0.725	49.603	17.511	348.334
roboden	525	4.594	9.604	0	0.262	1.419	4.445	81.716	4.196	23.819
labi	525	0.68	0.204	0.226	0.551	0.643	0.793	1.933	1.69	9.78
wage	525	46.018	26.72	3.897	21.945	44.352	64.948	114.252	0.252	2.177
log(1+offshore)	525	0.423	0.344	0.027	0.196	0.366	0.545	3.924	3.843	31.027
log(1+roboden)	525	1.095	0.976	0	0.233	0.883	1.695	4.415	0.999	3.615
dummy(labi)	525	0.659	0.474	0	0	1	1	1	-0.671	1.45
log(1+labi)	525	0.512	0.114	0.204	0.439	0.496	0.584	1.076	0.918	5.66
log(wage)	525	3.584	0.798	1.36	3.089	3.792	4.174	4.738	-0.959	3.133

Table A.14: Descriptive statistics for Other transport equipment

31-33 Furniture; other manufacturing; repair and installation of machinery and equipment [CM]										
Variables	**N**	**Mean**	**Standard Deviation**	**Min**	**First Quartile**	**Median**	**Third Quartile**	**Max**	**Skewness**	**Kurtosis**
offshore	540	0.132	0.103	0.027	0.07	0.101	0.156	0.742	2.723	12.793
roboden	540	4.561	15.222	0	0.155	0.798	2.381	112.456	5.106	28.894
labi	540	0.637	0.109	0.25	0.556	0.646	0.714	0.943	-0.377	3.309
wage	540	29.648	18.848	1.844	14.007	27.763	41.617	98.499	0.71	3.129
log(1+offshore)	540	0.121	0.082	0.027	0.067	0.096	0.145	0.555	2.242	9.63
log(1+roboden)	540	0.858	0.954	0	0.144	0.586	1.218	4.731	1.957	7.485
dummy(labi)	540	0.841	0.366	0	1	1	1	1	-1.862	4.468
log(1+labi)	540	0.49	0.068	0.223	0.442	0.498	0.539	0.664	-0.61	3.77
log(wage)	540	3.135	0.788	0.612	2.64	3.324	3.729	4.59	-0.735	2.991

Table A.15: Descriptive statistics for Furniture, other manufacturing, repair and installation

Descriptive Statistics: 35-39 Electricity, gas and water supply; sewerage, waste management and remediation activities [D-E] + 41-43 Construction [F] + 45-99 Total services [G-U]										
Variables	**N**	**Mean**	**Standard Deviation**	**Min**	**First Quartile**	**Median**	**Third Quartile**	**Max**	**Skewness**	**Kurtosis**
offshore	567	0.004	0.005	0	0.001	0.002	0.004	0.032	3.034	13.894
roboden	567	0.021	0.028	0	0.003	0.012	0.03	0.248	3.555	24.024
labi	567	0.519	0.067	0.311	0.476	0.536	0.566	0.653	-0.659	2.669
wage	567	29.347	15.81	1.891	16.08	28.092	39.727	84.14	0.48	2.925
log(1+offshore)	567	0.004	0.004	0	0.001	0.002	0.004	0.031	3.009	13.712
log(1+roboden)	567	0.021	0.026	0	0.003	0.012	0.029	0.221	3.178	20.069
dummy(labi)	567	0.376	0.485	0	0	0	1	1	0.513	1.264
log(1+labi)	567	0.417	0.045	0.271	0.39	0.429	0.449	0.503	-0.743	2.804
log(wage)	567	3.189	0.688	0.637	2.778	3.336	3.682	4.432	-1.008	3.751

Table A.16: Descriptive statistics for Electricity, Construction and Services

A.3 Histogram and kernel density estimation plots

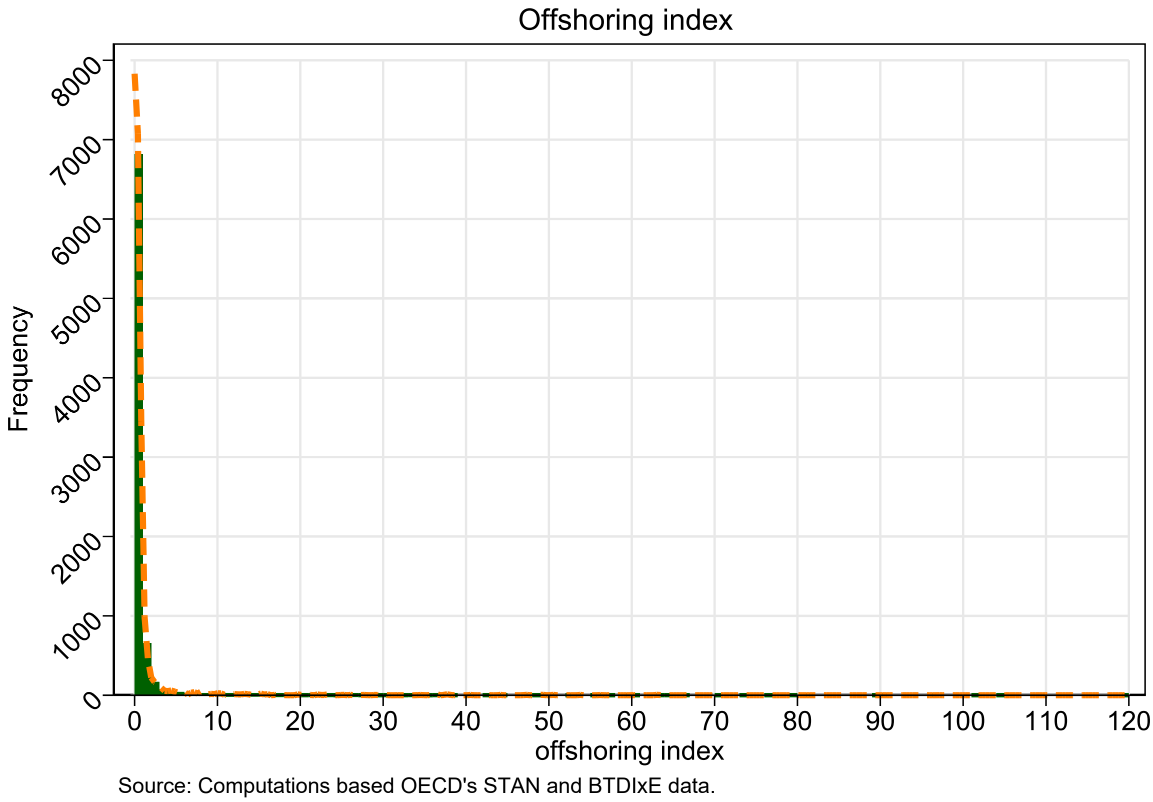

Figure A.1: Histogram and KDE for the distribution of the offshoring index

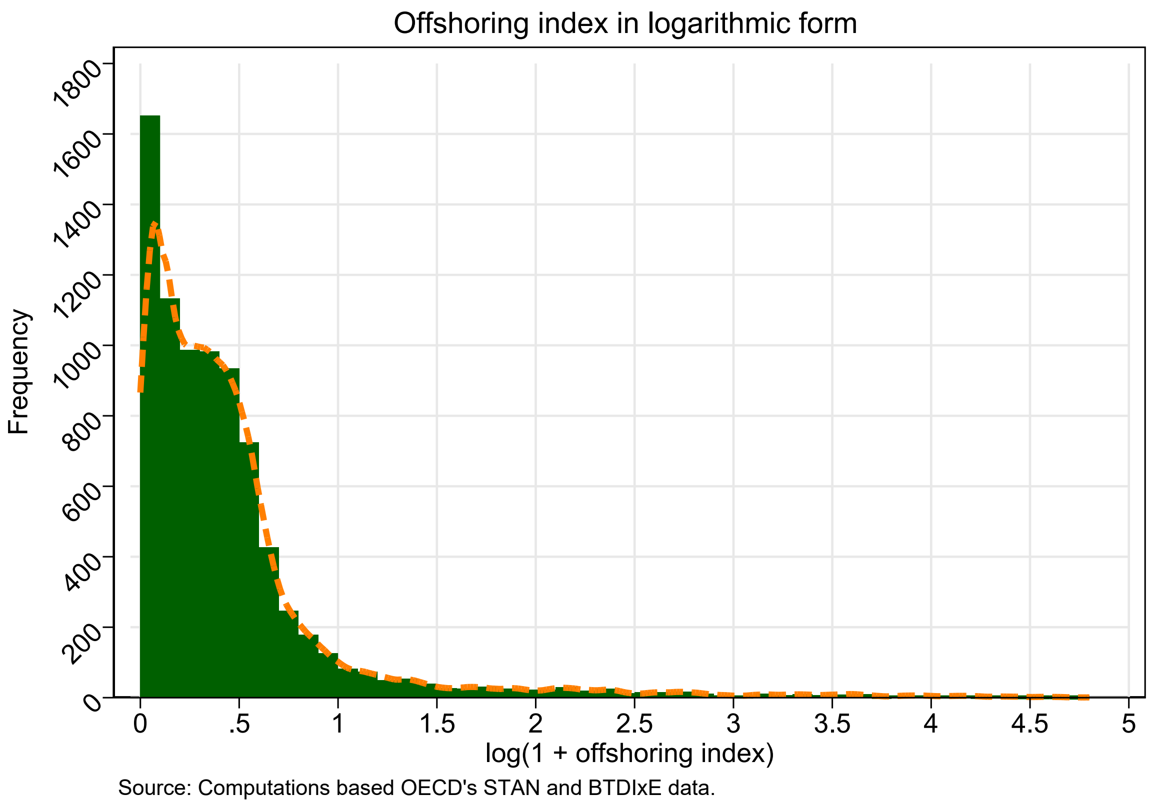

Figure A.2: Histogram and KDE for the distribution of the offshoring index in logarithmic form

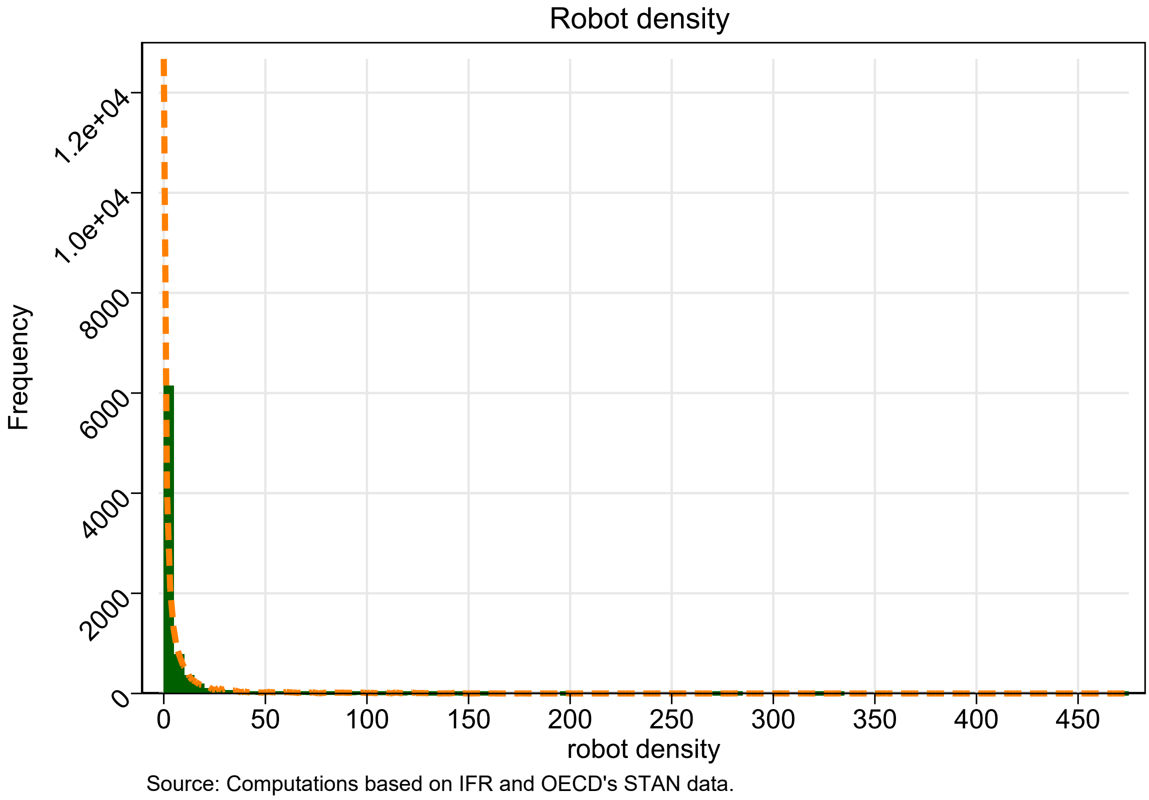

Figure A.3: Histogram and KDE for the distribution of robot density

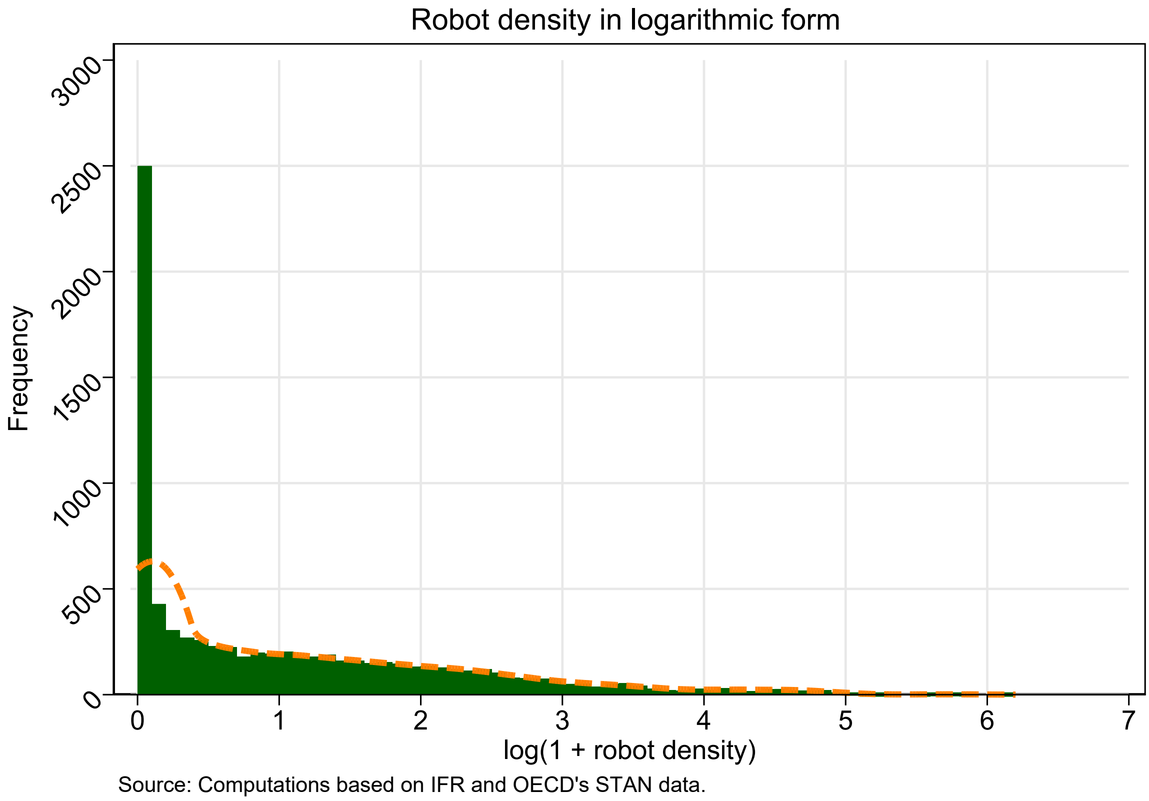

Figure A.4: Histogram and KDE for the distribution of robot density in logarithmic form

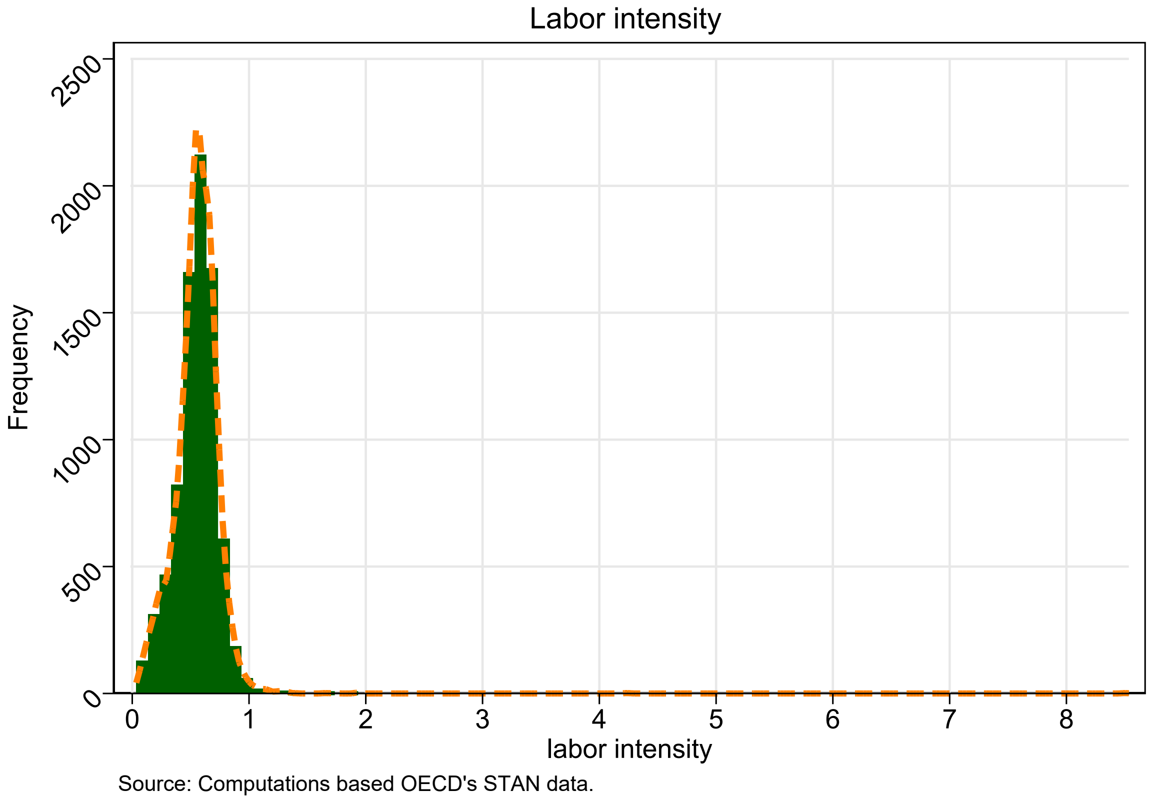

Figure A.5: Histogram and KDE for the distribution of labor intensity

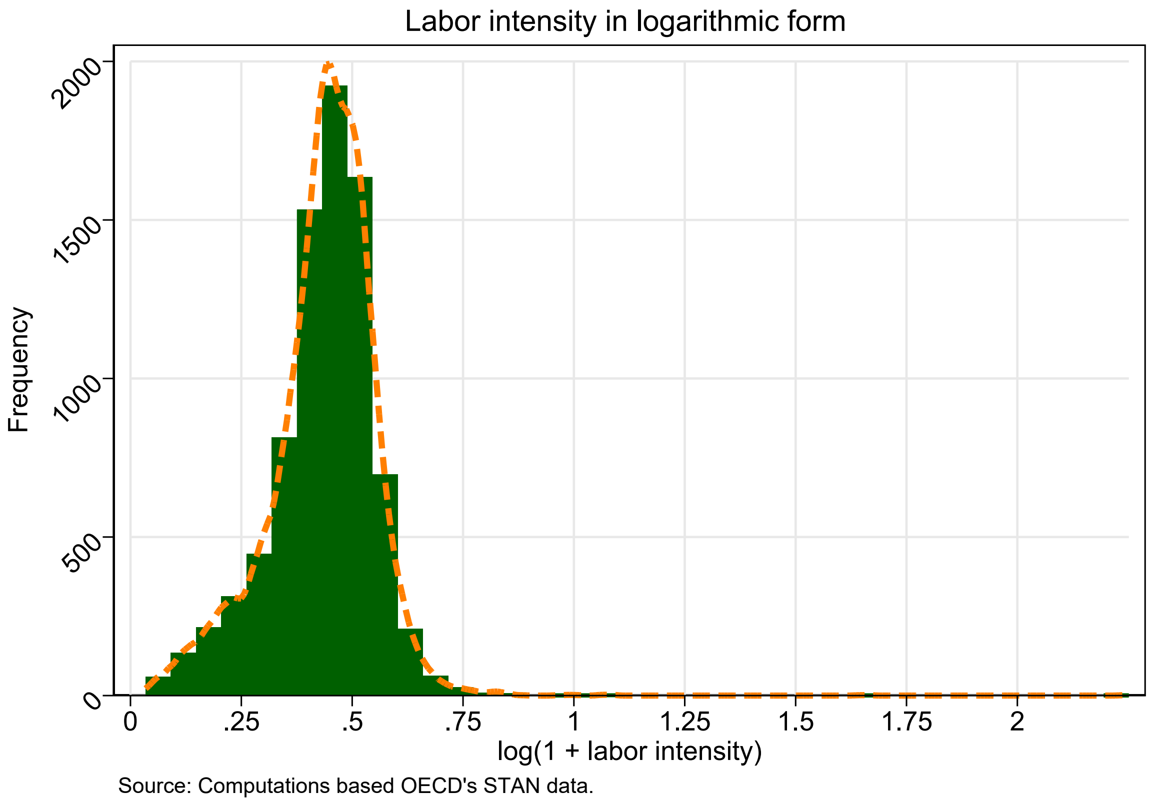

Figure A.6: Histogram and KDE for the distribution of labor intensity in logarithmic form

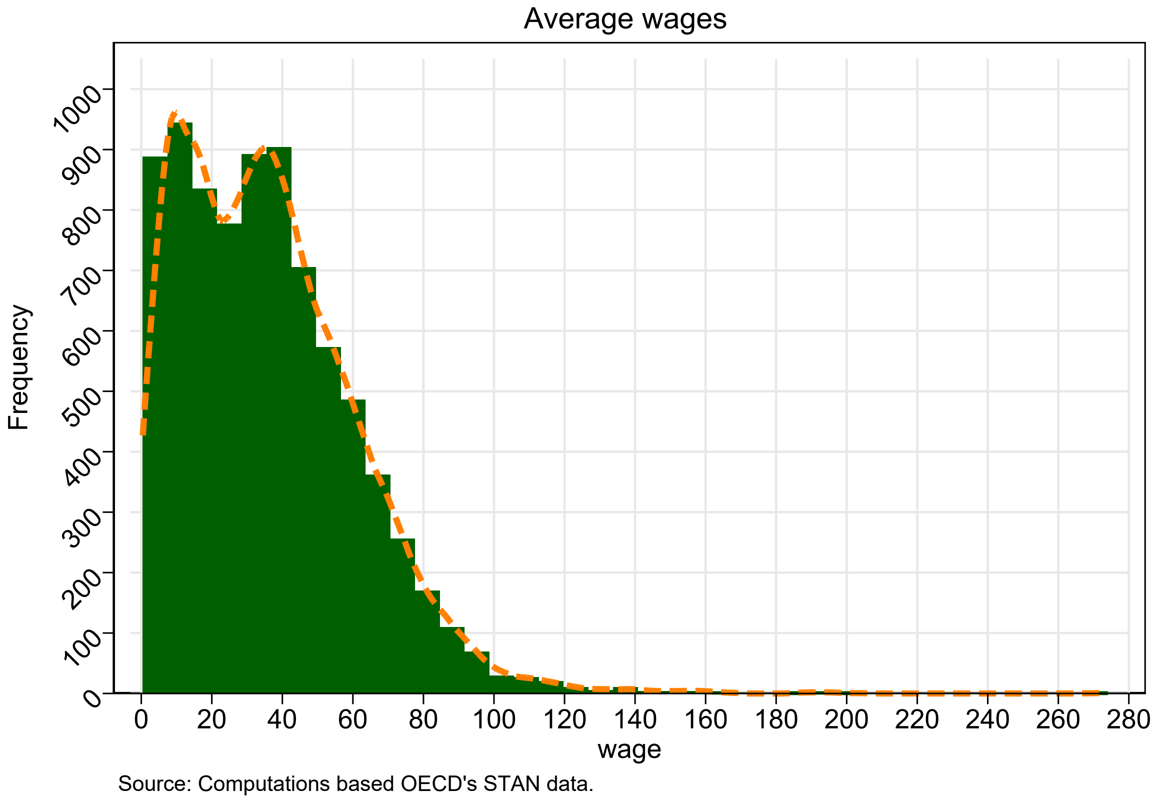

Figure A.7: Histogram and KDE for the distribution of the average wage

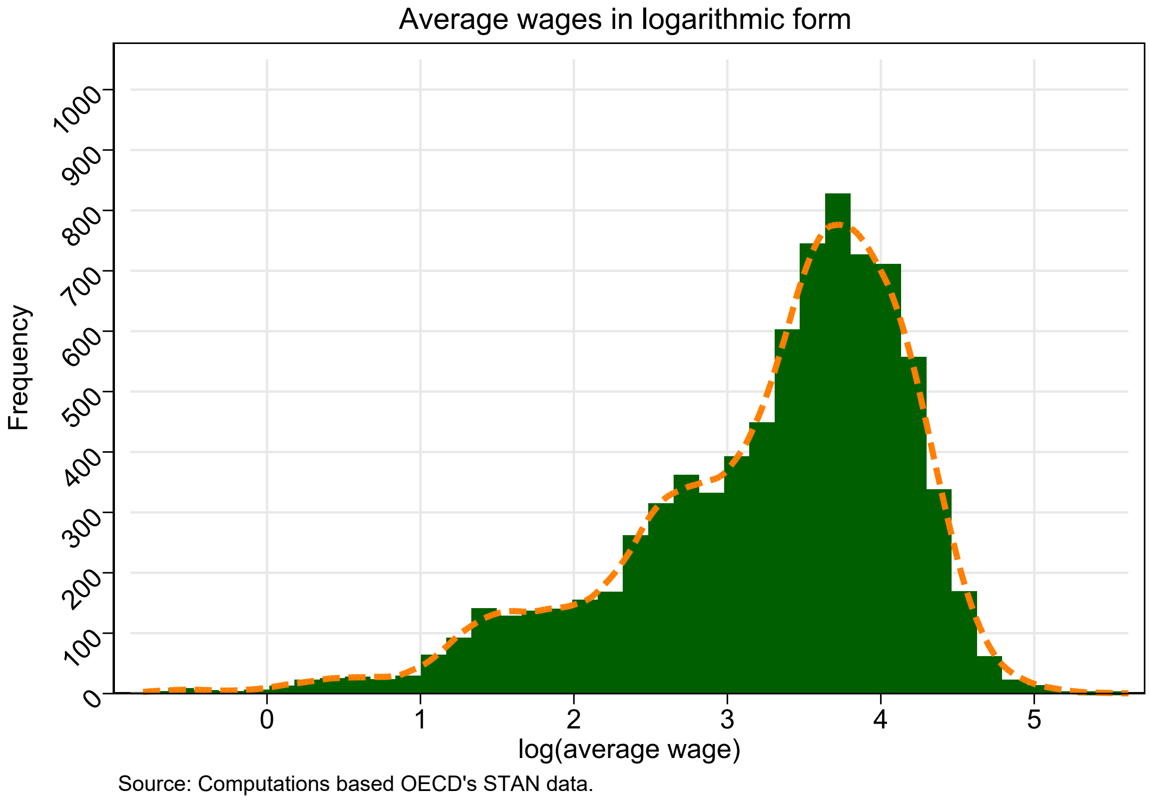

Figure A.8: Histogram and KDE for the distribution of the average wage in logarithmic form

A.4 Partial regression plots

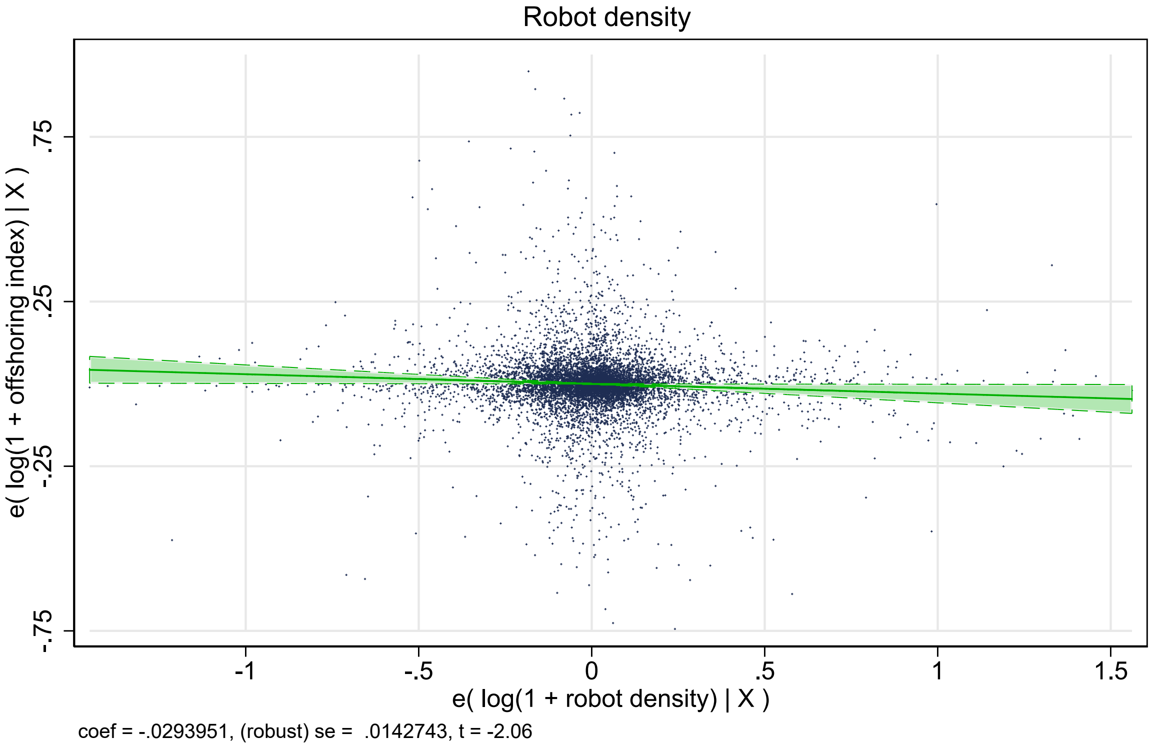

Figure A.9: Partial regression plot for robot density

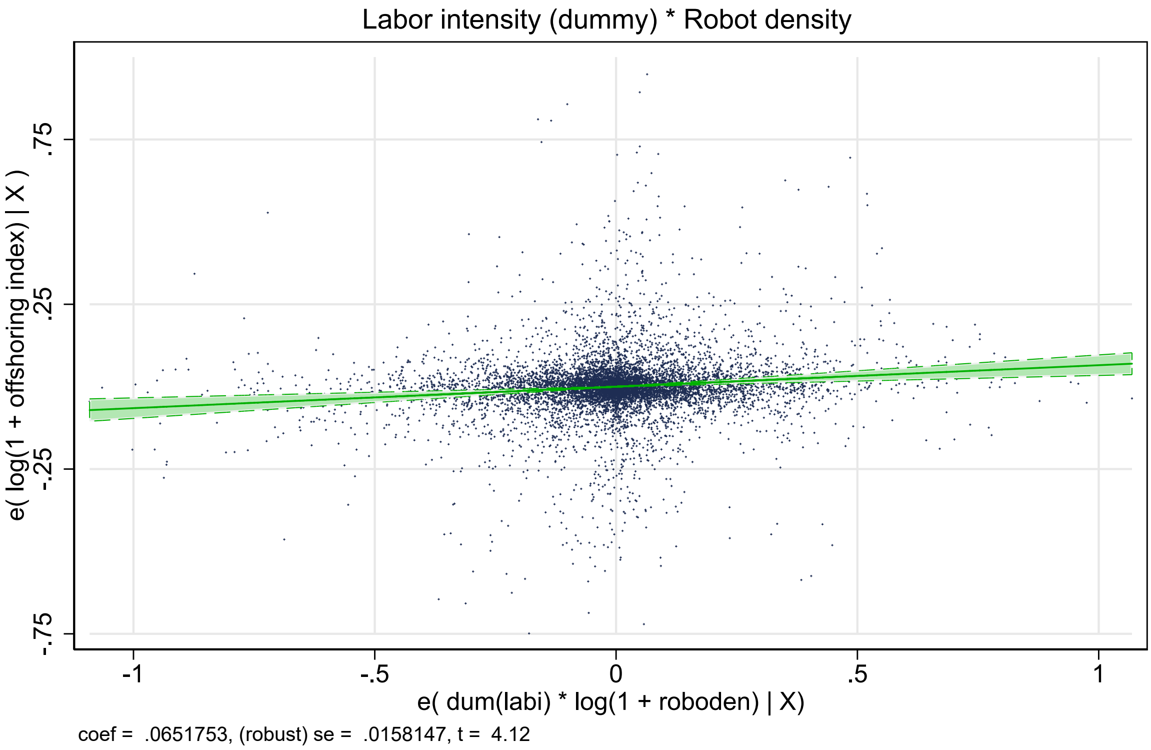

Figure A.10: Partial regression plot for the interaction term

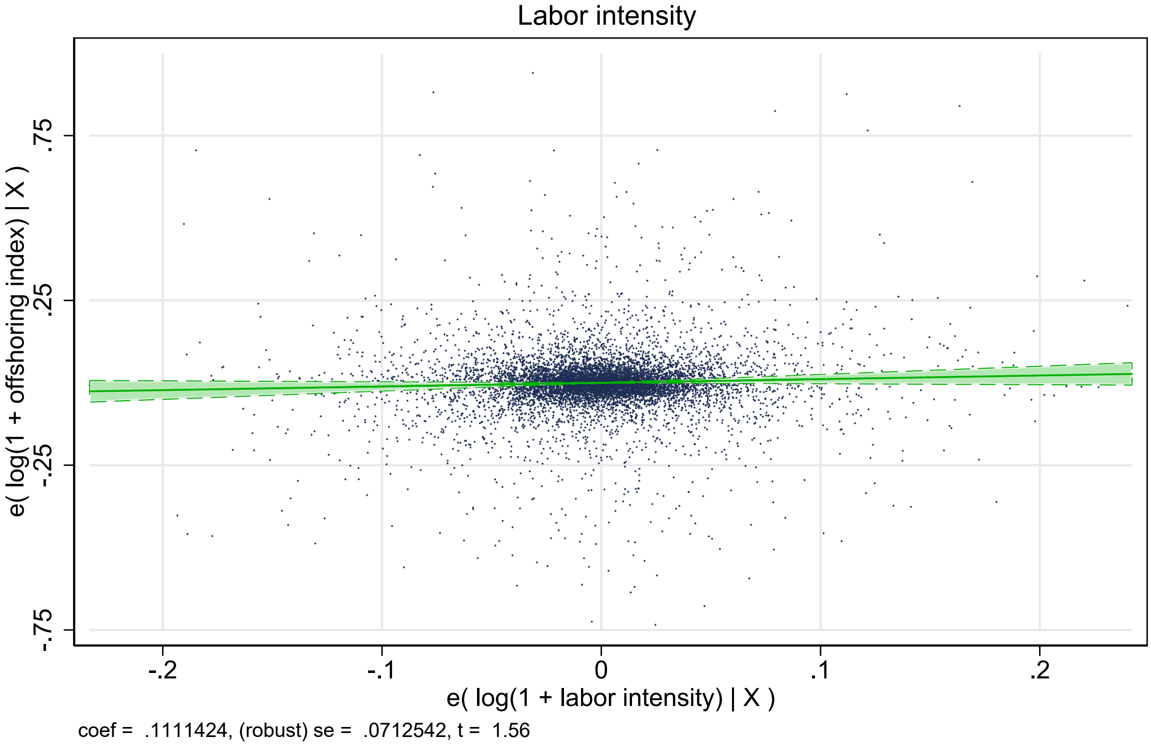

Figure A.11: Partial regression plot for labor intensity

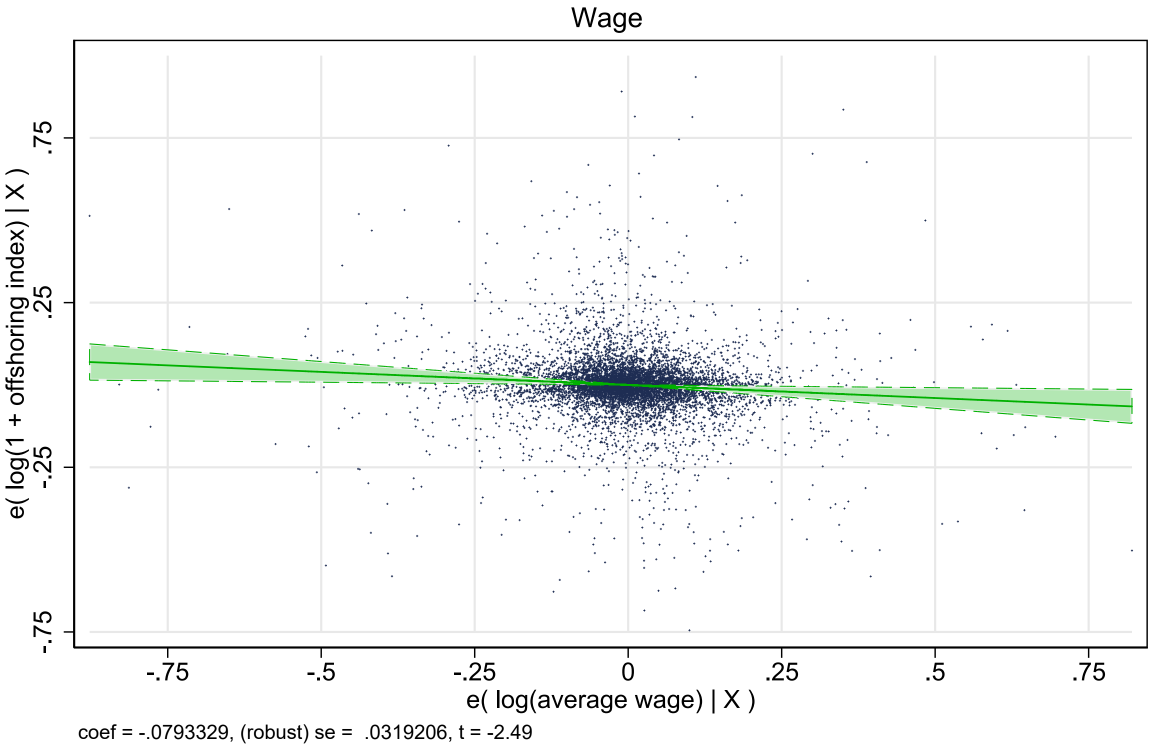

Figure A.12: Partial regression plot for average wages