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The Implications of Industrial Robots on the European Labour Market

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Abstract

As robots and other computer-assisted technologies substitute labour in an increasing number of tasks, there are increasing concerns to how this development will influence employment and wages. In this paper, we analyse the economic contributions of modern, industrial robots which are flexible, versatile and autonomous machines to determine how they affect the labour markets in Europe. The results indicate that the use of robots does influence European labour markets, suggesting that the level of employment is on aggregate level positively affected by robot exposure, which points to a dominating productivity effect. Still, our results suggest that the young and low-skilled labour groups are negatively affected, something that is offset by the positive effects observed for the older labour groups with higher educational attainment. The analysis only point to a limited number of robust and significant effects of robot exposure on wages, but these results suggest that robot exposure has a positive effect on wages. The results are based on the manufacturing sector, as the other sectors until now have been less influenced by industrial robots, and hence our findings may not be applicable for the economy as a whole.

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1.0 Introduction

Ever since the transition from hand production to machines run by steam power over 200 years ago, the labour market has adjusted to a continuous stream of technological developments. In recent times, technology has become increasingly sophisticated and proven to outperform workers in a wide range of tasks. This potentially leaves workers at risk of substitution, something that will be the core issue examined in our paper.

More specifically, our paper aims to investigate how different labour markets are affected by industrial robots and how these robot stocks influence the employment level and the wage level in Europe. The International Organization of Standardization (ISO, 2018) defines industrial robots as “automatically controlled, reprogrammable and multipurpose” (IFR, 2017). Each component of the definition is crucial for being labelled an industrial robot. For instance, if a robot is not reprogrammable or does not serve more than one single purpose, it will not be considered as an industrial robot.

In our thesis, Europe is represented by the G4 countries and Scandinavia. Hence, the countries included are France, Germany, Italy, the United Kingdom, Denmark, Norway and Sweden. In the analysis, we use different models – one pooled ordinary least square (OLS) regression, one fixed effects model and one two stage least square (TSLS) regression using the United States robot stock as our instrument variable (IV).

We use panel data on robot adoption within industries in the 7 countries from 2008-2015 and include robot adoption data for the United States as our instrument. By examining these countries, we attempt to analyse the effects that industrial robots have had on European labour markets in the time span of our data sample. This will be done by using a model where robots compete against human labour in the production of different tasks, inspired by the paper “Robots & Jobs: Evidence from US Labor markets” by Acemoglu and Restrepo (2017a).

There are broadly three approaches to assess the impact of automation on employment and wages. The first is to investigate the impact of technological breakthroughs on labour. One could for instance see that the introduction of the T-

Ford in 1908 led to a reduction in jobs within transportation, as one car could transport much more efficiently than one horse-carriage. However, there was also a positive impact on employment as more jobs were created in response to this increase of cars on the road and the increased range of transportation. Where there was a decline in jobs within transportation, there was an increase in the number of jobs within the service sector, as these cars needed services such as gas stations, motels and fast-food restaurants. There exists a wide range of evidence that past industrial revolutions have had a dominating displacement effect in the short run. However, as the markets adapt to these changes, the productivity effect has prominently dominated in the longer run with positive labour market effects. The problem by using this approach, as we will discuss in the background section, is that compared to the previous industrial revolutions, the Industry 4.0 transition is happening at a much faster pace and in a larger scale. Hence, this approach might not be able to capture the true impact of robot exposure.

A second approach to assess the impact of automation would be to assess the risk of replaceability for different tasks and occupations, along the lines of Schwab (2017), Frey and Osborne (2017) and Arntz, Gregory, and Zierahn (2016). This will also be discussed further in the next section, though this approach is more suitable to measure the displacement effect than the productivity effect as it does not take into account that new machines might even expand the employment level. The labour market impact of new technologies does not only depend on where they are implemented, but also on how the economy as a whole adjust to these changes, as illustrated by Acemoglu and Restrepo (2017a) in their theoretical model. In order to capture both these effects, it is necessary to assess the equilibrium impact of industrial robots on the labour market.

This is where the third approach comes in, which is the method used by Acemoglu and Restrepo (2017a); Chiacchio, Petropoulos, and Pichler (2018); Graetz and Michaels (2015). As stated by Acemoglu and Restrepo (2017a), a higher density of robots might affect employment in two main directions: Either by a displacement effect or by a productivity effect. The former being that workers are directly displaced from tasks that they were previously performing, while the latter is the increase of labour demand due to technological advances.

As these effects oppose each other, we will assess how these effects impact the labour market in equilibrium.

This model will attempt to demonstrate how the use of robots may reduce, or increase, the level of employment and/or wages by regressing the change in employment and wages on the exposure to robots. The exposure to robots is defined as the national penetration of robots into each industry and the distribution of employment across industries (Acemoglu & Restrepo, 2017a).

2.0 Literature review

2.1 Background

In 1930, John Maynard Keynes made a famous prediction about the rapid technological progress that was to follow for the next 90 years, while also conjecturing that "We are being afflicted with a new disease of which some readers may not have heard the name, but of which they will hear a great deal in the years to come – namely, technological unemployment" (Keynes, 1933). Leontief (1952) foretold similar scenarios of future employment decades later, by writing: "Labor will become less and less important… More and more workers will be replaced by machines. I do not see that new industries can employ everybody that wants a job". Although these predictions failed to materialise in the decades that followed them, major breakthroughs in technology have been made in recent years, where we can see Google's autonomous cars logging several miles on American highways or IBM's Watson trumping the best human *Jeopordy!* players.

As digital technologies make robots more precise and able to process vast amounts of data and perform many different tasks, such as surgery, their application can enrich our lives but also upend many professions (Soldani, 2016). On the one hand, you have researchers that believe these digital technologies will, as Keynes and Leontief foretold, leave many people unemployed (Autor, 2017; Ford, 2015). On the other hand, you have researchers that believe these employees can now be reallocated to other parts of the economy or provide a transformation in their work assignments within their industry (Lawrence, Roberts, & King, 2017).

Schwab (2017) ranks different occupations according to how susceptible they are to automation, and more evidence has been published in recent years when it comes to the automation of low-skill and medium-skill occupations and how this contributes to wage inequalities and employment polarization (Autor, 2010; Goos & Manning, 2007; Goos, Manning, & Salomons, 2009; Tüzemen & Willis, 2013). Some figures suggest that as much as half of today's current occupations are at risk of automation in the next couple of decades (Schwab, 2017). Autor (2017) and Manyika et al. (2017) provide similar figures. On the other hand, researchers such as Arntz et al. (2016) find that only 10 per cent of occupations in the United Kingdom, one of the countries in our sample, are at high risk of automation.

Even though variations of these figures are widely reported, there is little systematic evidence of the equilibrium impact of these new technologies, and the use of robots in particular, on wages and the level of employment. Most research investigates the maximum feasibility of what industries and/or tasks that could be automated within the next coming years, but do not calculate the equilibrium impact of this automation. Even though we might see technology in the coming years that could potentially displace labour in a growing number of tasks, it is not given that firms will choose to automate these tasks. Given the available technology, firms will have to consider the relative cost of labour against the relative cost of the technology and how much wages might change in response to the mere threat of technology. In addition, if some tasks are automated, this might move labour from one task to another within that industry or other industries might soak up the freed-up labour from tasks now performed by robots. Another important feature of the new technology is that it might enhance productivity, which could expand the need for employees instead of replacing it. And there might, based on the new technology, be developed new task that we do not see today.

2.2 Literature review

We have chosen to extract elements of three different papers that have adopted this third approach as they all focus on the impact of industrial robots. The reason why we have chosen to focus on industrial robots is that there is quality data available for these types of robots.

2.2.1 "Robots & Jobs: Evidence from US Labor Markets"

We have chosen to follow much of the same methodology as "Robots & Jobs: Evidence from US Labor Markets", and to use the same data sources where these have been available. Acemoglu and Restrepo's paper analyses the effects on labour markets with respect to the increases in industrial robot exposure in the United States between 1990-2007. They developed a model in which robots compete against human labour in the production of different tasks and attempt to show how robots might affect wages and employment. This is done by regressing the change in employment and wages on the exposure to robots in each labour market within the United States. By using this approach, they are able to estimate large and robust negative effects of robots on both employment and wages in different commuting zones throughout the United States. According to their estimates, one more robot per thousand workers reduce the employment to population ratio by about 0.18-0.34 percentage points and wages by 0.25-0.5 percent (Acemoglu & Restrepo, 2017a).

2.2.2 "Robots at Work"

This paper by Graetz and Michaels (2015) is useful as it has another perspective on the theme and was the first paper that analysed the economic contributions of modern industrial robots. They used novel panel data from 1993-2007 on robot adoption within industries in 17 different countries, and two new instrumental variables that relied on the comparative advantages of robots in doing specific tasks. One being data on "robot application" which classified the tasks performed by robots and the other instrument involved "reaching and handling", which mainly looked at advances in technology when it comes to the use of robotic arms. Their findings suggested that an increased density of industrial robots contributed to approximately 0.36 percent of annual labour productivity growth, as well as raising total factor productivity and lowering prices of output. Their estimates suggested that total employment was not reduced significantly due to robots, even though they reduced the employment share of low-skilled workers.

2.2.3 "German Robots – The Impact of Industrial Robots on Workers"

This paper is useful as it looks directly at one of the countries within our sample. They find the impact of increased exposure to robots on the careers of individual manufacturing workers, as well as the equilibrium impact across industries and local labour markets in Germany. They find no evidence that the industrial robots cause a reduction in total jobs, but instead that they affect the composition of aggregate employment. Their results show that one additional robot displaces two manufacturing jobs. In the period between 1994 and 2014, this accounted for almost 23% of the overall decline in manufacturing employment. However, this loss in jobs was fully offset by an increase of jobs in the service sector. In addition, they found that the workers within manufacturing that is thought to be at the highest risk of displacement are more likely to remain within their original workplace – though often performing different tasks than before. Moreover, they found that the decline in aggregate employment within manufacturing was driven by fewer job opportunities within this industry for young labour market entrants. However, the increased job stability for those already employed is offset by the cost of lower wages. This is primarily shown for medium-skilled workers, and they also find that high-skilled managers gain. Their findings hence suggest that robots raise labour productivity, but not wages – contributing to the decline of the labour income share (Dauth, Findeisen, Suedekum, & Woessner, 2018)

3.0 Theoretical Model

The theoretical model used in this papers stems from Acemoglu and Restrepo (2017a). They present a model that exposits the potential effects of robot exposure on employment and wages, and thereby derives the estimating equations used for empirical analysis. The model we will be using ignores any interaction between labour markets.

They propose that the impact of robots on employment and wages is given by:

Employment: $dlnL_c = -\frac{1+\eta}{1+\varepsilon}\sum_{i\epsilon I} \ell_{ci} \frac{dM_i}{1-M_i} + \frac{1+\eta}{1+\varepsilon}\pi_c \sum_{i\epsilon I} \ell_{ci} \frac{s_{icL}}{s_{cL}} \frac{dM_i}{1-M_i}$

Wages: $dlnW_c = -\eta \sum_{i\epsilon I} \ell_{ci} \frac{dM_i}{1-M_i} + (1+\eta)\pi_c \sum_{i\epsilon I} \ell_{ci} \frac{s_{icL}}{s_{cL}} \frac{dM_i}{1-M_i}$

These propositions characterise the total equilibrium impact of robots. The first term defines the general equilibrium version of the displacement effects (that robots substitute employees). The second term is a combination of the price-productivity effect and the scale-productivity effects (hereafter called the productivity effect). These terms are expressed as a function of the changes in robot technology. Our model is a simplification of these propositions and will be presented below. There are clear similiarities between the models we are proposing for employment and wages and the ones proposed by Acemoglu and Restrepo (2017a). We are not differing between the productivity and the displacement effects in our model, and do not include local labour supply elasticities ($\frac{1}{\eta}$ and $\frac{1}{\varepsilon}$), neither are we including the cost share parameters $s_{icL} and\ s_{cL}$ as these were not obtainable.

3.1 Employment

Our main specification uses the exogenous exposure to robots between 2008-2015 on the right-hand side, and should therefore be interpreted as the reduced-form of:

$$d\ln L_c = \beta_c^L \sum_{c\epsilon C} \ell_c \frac{dR_c}{L_c} + \epsilon_c^L$$

Throughout this paper, unless stated otherwise, our main specifications are in log changes. The share of employment in country c is denoted by ℓ_c. The change in robot exposure is denoted by $\frac{dR_c}{L_c}$. Hence, advances in the technology of robotics will have a greater effect in countries that have a greater share of their employment in the industries that are increasing their exposure to robots.

3.2 Wages

Our main specification uses the exogenous exposure to robots between 2008-2015 on the right-hand side, and should therefore be interpreted as the reduced-form of:

$$d\ln W_c = \beta_c^W \sum_{c \epsilon C} \ell_c \frac{dR_c}{L_c} + \epsilon_c^W$$

Where the notatations are the same as for the employment specification.

4.0 Data

We have conducted our research by using data concerning robot stock and labour market data for the countries included in our research sample. In addition, we used data for robot exposure in the United States to perform the TSLS estimation.

The data was disaggregated by gender, age and education attainment in such a way that we were able to derive the labour market outcomes for different demographic groups. Age segments were classified in 3 groups: 15-29, 30-54 and 55+ respectively. Education attainment segments were also classified in 3 groups: Low, Medium and High respectively. The three different levels of education attainment are specified accordingly; Low indicates a high school diploma or less. Medium indicates either a bachelor's degree, some college or an associate degree. High indicates a master's degree or higher.

This distribution provided us with 18 different demographic groups. Consequently, we had 126 observations per year which yielded 1008 observations in total. The use of demographic cells allowed us to potentially isolate the changes in wages that were due to changes in the composition of the labour force which is crucial when estimating the wage effects. This could be exemplified by a situation where we experience a decrease in highly educated employees, which would mechanically reduce the wage level.

4.1 Sample sources

Our main source of data on robots is the International Federation of Robotics (IFR, 2017), which compiles data from national robot federations on industrial robots. These data sets consist of robot deliveries by industry, country and year, and cover about 90 percent of robots sold globally in different sectors with the following classifications:

A-B - AGRICULTURE, FORESTRY AND FISHING
C – MINING AND QUARRYING
D – MANUFACTURING
E – ELECTRICITY, GAS AND WATER SUPPLY
F – CONSTRUCTION

P – EDUCATION/RESEARCH/DEVELOPMENT
90 – ALL OTHER NON-MANUFACTURING BRANCHES
99 – UNSPECIFIED

The International Federation of Robotics (IFR) measures robot deliveries based on the definition put forward by the ISO. There are some shortcomings in the data, as about 30 percent of the robots are unclassified and hence not assigned to either of the classifications. We will use the same approach as Acemoglu and Restrepo (2017a) and allocate these unspecified robots to industries in the same proportion as the classified data. As we had data from 1993-2015 on the robot deliveries, we had to aggregate these figures in order to get the robot stock in our sample period.

Since our analysis focused on the impact of robots on employment and wages we also exploited labour markets data for our sample. For the labour market data, our main source was the EU KLEMS Growth and Productivity Accounts (KLEMS, 2017), where we collected labour data for Denmark, Germany, Great Britain, Italy, France and Sweden to measure the industrial robots per thousand workers by country, industry and time. Similar labour data for Norway was collected from Statistisk Sentralbyrå (SSB, 2017a, 2017b). Employment is measured by the employment to population ratio. Wages are measured by total compensation in the economy divided by the number of employed workers. The labour data includes the share of employment type and the share of labour compensation for each demographic group in such a way that we are able to differentiate between the respective wage and employment level of each individual group.

4.2 Sample Selection

IFR and EUKLEMS/SSB data use different industry classifications. We therefore had to merge some industries to consistently match the data sets, which we did by using the least comprehensive industry classification as a template for merging the others, and this was the data provided by the IFR.

The reason why we start our analysis in 2008 is due to the data restrictions that made analysis with respect to gender, education and age possible. This data was only available from 2008. We should keep in mind that the cyclical fluctuations created by the financial crisis may present confounding effects for our estimation. There is reported a smaller increase of robot penetration in 2008-2015 than during the 1990s and early 2000s. This might be due to the decrease in demand during the financial crisis and fewer opportunities for firms to automate. Hence, our results should be interpreted with some caution. We end our analysis in 2015 since this is the last year covered by the IFR.

4.3 Data Manipulation

Nominal variables, such as labour compensation, are reported in units of local currency in the EU KLEMS data. When comparing these variables across countries, we therefore look at the growth in these numbers to avoid converting all currencies.

4.4 Descriptive statistics

	Mean	Standard Deviation	Min	Max
Shares of employment type in Manufacturing	0.056	(0.051)	0.001	0.282
Shares labour compensation type in Manufacturing	0.056	(0.057)	0.001	0.291
Relative change in employment	-0.016	(0.032)	-0.138	0.025
Relative change in wages	0.007	(0.033)	-0.105	0.055
Relative change in Robots	0.029	(0.170)	-0.409	0.577
Observations	1566			

Table 1 – Descriptive Statistics

4.4.1 Dependent variable 1: Employment

The mean for relative change in employment is –0.016. The minimum and maximum values are –0.0138 and 0.025 respectively. This indicates that within the manufacturing industry, there has been a decrease in the employment level during the period 2008-2015.

4.4.2 Dependent variable 2: Wage

The mean for relative change in wages are 0.007. The minimum and maximum are –0.105 and 0..055 respectively. This indicates that within the manufacturing industry, there has been a slight increase in the wage level during the period 2008-2015.

4.4.3 Independent variable: Robot exposure in Europe and Robot exposure in the US

The measure of robot exposure is defined as the stock of industrial robots per thousand employees in a certain industry and country:

$$Robot\ Exposure_{Europe} = \frac{Number\ of\ Industrial\ Robots}{Number\ of\ Employees\ in\ the\ Work\ Force}$$

This measure is similar to that used by (Acemoglu & Restrepo, 2017a). Further, we have, as Graetz and Michaels (2015) assumed a depreciation rate of ten percent.

Similarly, the measure of robot exposure in the US is defined as:

$$Robot\ Exposure_{US} = \frac{Number\ of\ Industrial\ Robots}{Number\ of\ Employees\ in\ the\ Work\ Force}$$

One shortcoming of using this as an instrumental variable is that data from IFR on industrial robots only covers a limited period of the period used to construct the robot exposure variable. While aggregate data for the United States is available from 1993, industry breakdowns are only available for the period from 2004 to 2015. We have therefore chosen to construct estimates for the missing years. This is done by deflating the 2004 stocks by industry. Another shortcoming is that the IFR only reports the overall stock of robots for North America, not solely for the US. However, the US accounts for more than 90 percent of the North American market for industrial robots and should therefore provide us with reasonable figures for constructing our instrumental variable.

4.4.4 Control variable 1: Growth of Information and Communication Technology (ICT) capital

The rapid progress in the evolution of ICT has become increasingly more evident and has facilitated the use of machinery and equipment which performs, or at least assist, in tasks that were previously performed by workers. Similarly to industrial robots, this may potentially lead to displacement or productivity effects within the labour markets. If not taken account for, this might lead to omitted variable bias where the dependent variable are correlated with the error term.

To control for these effects, we used data on ICT capital services collected by EU KLEMS (2017) at the same level as the rest of our data. Since Norway is not covered by EU KLEMS, corresponding data for Norway was collected from SSB (2017b).

4.4.5 Control variable 2: Changes in manufacturing output

Along with technological change, global competition has been found to be a significant driver of the dynamics in the labour force. As many of these changes are due to changes in output and not due to technology, we will include a control for the change in manufacturing output. Data was once again collected from the OECD (2018) and SSB (2017a).

4.5 Validity and quality of data used

Data on output, level of ICT, wages and employment used in the EUKLEMS 2017 release is consistent with official statistics available from Eurostat. Hence, when comparing data between EU KLEMS and Eurostat, this data provides strong validity in the comparability of the series across countries. The data on Norway, collected through SSB, is harder to validate, as there are no comparable statistics available.

Looking at the data on industrial robots, the robot statistics provided by IFR are based on consolidated world data reported by robot suppliers, something that ensures the validity of the quality of the data. Statistics of the national robot associations of North America (RIA, 2018), Germany (VDMA, 2018), Italy (SIRI, 2018) are some of the contributors to the IFR data, and hence these data sets should be fairly accurate for the 7 countries we are examining, as well as our instrumental variable. Further, the studies in the literature review, all investigating the same topic as this thesis have used the same data sources.

5.0 Methodology

To guide our empirical analysis, we have developed a simple model of robot exposure, which is a simplification of the model used by Acemoglu and Restrepo (2017a) and describes the relationship between exposure to robots and logged changes in wages and employment.

We have chosen to use panel data in our modelling as it allows for individual heterogeneity and therefore enables seperation of the effects within our demographical groups. In addition, panel data allows us to control for variables that change over time, something that made it a good choice for this paper. Further, we have chosen a fixed-effects model, as we are only interested in analysing the impact of variables that vary over time, i.e. wage and employment level.

Following the methodology of Acemoglu and Restrepo (2017a), we were interested in whether the results from the US Labour markets were applicable for European Labour markets. We were also interested in how these effects are in a more recent time span, as much have changed within technology since 2007. We will focus on the industry that is the most exposed to robots, as seen in Figure 1. Here we can see that Manufacturing is the most exposed sector, and the one that will give us the best basis for identifying the aggregate implications of our estimates.

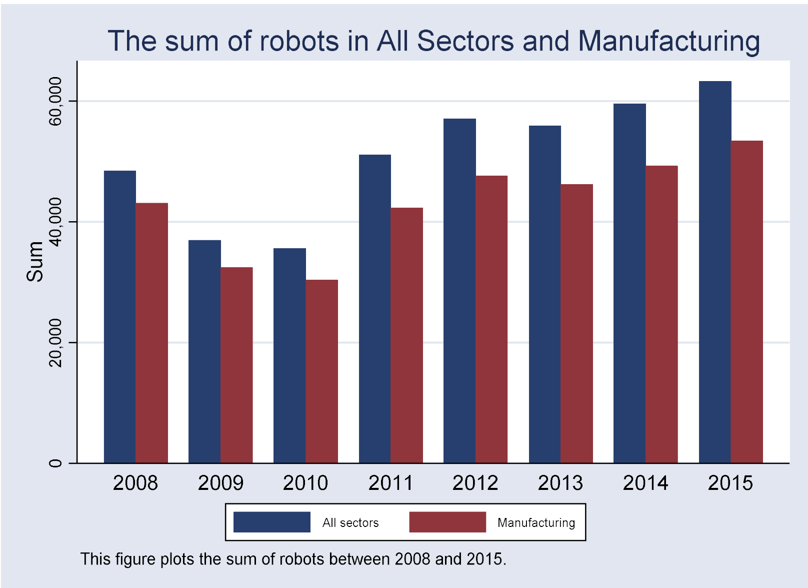

Figure 1 - The Share of Industrial Robots in Manufacturing

5.1 Identification strategy

Our empirical analysis addresses two main hypotheses. The first hypothesis being whether the exposure of industrial robots has negative effects on employment. The second hypothesis being whether the exposure of industrial robots has negative effects on wages. The causal relationship between robot exposure and the dependent variables is either positive, negative or insignificant.

The identification strategy of the paper deals with endogeneity concerns described in previous studies. To eradicate these issues, we will use a two stage least square (TSLS) framework. This will be addressed in section 5.3.

Further, we have chosen to look at sub-groups of the population in addition to the aggregate findings, in order to identify how each demographical group is affected by exposure to robots. As we believe that the effects of robot exposure is different for these groups, estimating different regression models for each sub-group using interaction variables instead of indicator (dummy) variables allows for more hypotheses to be tested and a greater understanding of the relationships between variables.

5.2 OLS Regression

In order to estimate the effect of robot exposure on employment and wages, we start by regressing the following equation:

$$Y_{c,t} = \alpha * Robots_{c,t} + \beta * X_{c,t} + \varepsilon_{c,t}$$

Where $Y_{c,t}$ either takes the form of change in employment or the wage level. Robots is the "Exposure to Robots" variable, $\varepsilon_{c,t}$ is the error term, and $X_{c,t}$ is the demographic variable referring to gender, age and education. The endogeneity concerns are that the regressor, Exposure to robots, might be correlated with the error term using this specification.

5.3 Fixed-Effects model

A fixed effects model explores the relationship between the predictor and the outcome variables within countries and/or regions. Each of these countries/regions, have their own individual characteristics that might influence the predictor variables, such as gender, educational attainment or age. The rationale behind the assumption of the correlation between the countries/regions' error term and predictor variables is that a fixed effects model assumes that something within the country/region might impact, or bias, the model and that this is something that we need to control for.

A fixed effects model will remove the effect of the time-invariant characteristics in such a manner that we can examine the net effects of the predictors on the outcome. Another important feature is that the time-invariant characteristics are unique and that they should not be correlated to other countries' characteristics, hence neither the error term nor the constant term should be correlated with the other (Torres-Reyna, 2007). To assess whether this holds, we needed to perform a Hausman-test. This test assessed whether a fixed effects model or a random effects model was the most suitable. Using this test, we found that when regressing the employment level, the fixed model was preferred as the unique errors were correlated with the regressor, which resulted in a chi-value of 0.83 – clearly higher than the threshold of 0.05. When regressing the wage level, we found a chi-value of 0.47, which is also much higher than the threshold. We therefore found that for both our TSLS specifications, the fixed effects model was preferred. These results can be found in Table 6 in the Appendix.

5.4 Two-stage Least Square

In order to deal with the endogeneity concern mentioned in our OLS specification, we chose to examine our results using a two-stage least square (TSLS). In laymans terms, something that is related to our wage or employment variable might also be related to our Exposure to robots variable. This could be due to many factors, not all easily available to include in our model. First, some industries may be adopting robots in response to other changes that they are undergoing, something that could directly impact their demand for labour. Secondly, any shock to labour demand in a region affects the decisions of the industries located in that region, including their decisions of adopting more robots (Acemoglu & Restrepo, 2017a).

In order to address this problem, and identify an isolated effect, we address these issues by using the inverse approach of Acemoglu and Restrepo (2017a). As they used Exposure to robots in Europe as an instrument for the US, we are using Exposure to robots in the US as an instrument for Europe.

Thus, by combining the European and the US data, we compute the TSLS estimate for our main dependent variable's coefficients. As both the US and Europe are advanced economies, the use of an IV allows us to focus on the variation between regions that have been experiencing much of the same trends. For instance, robot usage in Europe might have been acelerated as a result of expansion in robot usage in other advanced economies. As mentioned in Acemoglu and Restrepo (2017a), there is no guarantee that using exogenous exposure to robots is a definite cure for all kinds of endogeneity concerns. Such concern could be in the form of rising wages or import competition, something that would affect both European and US industries. Although we do believe that using this variable as an instrument provides a better basis for reaching an unbiased result than our OLS specification.

The intuition behind the TSLS is to reduce the bias introduced when our regressor $X_{i,t}$ is correlated with the error term $\varepsilon_{i,t}$. We want to divide the Exposure to Robots variable into one part that is correlated with the error term and one part that is uncorrelated with the error term. Subsequently, we use the uncorrelated part and disregard the part that introduce bias. In effect, we identify the uncorrelated term and use this exogenous variation in the regressor to produce more consistent estimates (Angrist & Pischke, 2014).

The implementation of our TSLS includes a first stage where we regress exposure to robots in Europe, with notation Ď, on our instrument - Exposure to robots in the US, with notation Z, and keep the fitted values Ď. Hence, we identify the part of Ď that is uncorrelated with the error term. This is formally presented in equation (1). Equation (2) presents the reduced form.

$$\check{D}_{c,t} = \alpha_1 + \phi Z_{c,t} + \gamma_1 A_{c,t} + \varepsilon_{c,t} \quad (1)$$
$$Y_{c,t} = \alpha_0 + \rho Z_{c,t} + \gamma_0 A_{c,t} + \epsilon_{c,t} \quad (2)$$

Because $\alpha_1 + \phi Z_{c,t}$ is the part of $\check{D}_{c,t}$ that is predicted by $Z_{c,t}$ and $Z_{c,t}$ is exogenous, we have identified an unproblematic variation of Ď.

In the second stage we replace Exposure to robots in Europe with our fitted values from the first stage. We regress our two dependent variables - employment and wages, $Y_{c,t}$, on the fitted values Ď. The second stage is formally presented in equation (3).

$$Y_{c,t} = \alpha_2 + \lambda_{2SLS} \check{D}_{c,t} + \gamma_2 A_{c,t} + \acute{\varepsilon}_{c,t} \quad (3)$$

For our instrument to be credible it must satisfy three key assumptions. Firstly, the instrument must satisfy the relevance criterion. The instrument Z should have a causal effect on the treatment variable. This is assessed in the first stage and implies that $\phi > 0$. We are able to test the relevance criterion statistically by checking for correlation between exposure to robots in the US and exposure to robots in Europe. The correlation coefficient between exposure to robots in the US and exposure to robots in Europe is 0.76 which satisfies $\phi > 0$ and subsequently also satisfies the relevance condition.

Secondly, the instrument must also meet the exclusion criterion. This implies that the instrument can only affect the outcome through one single channel. The exclusion criterion cannot be statistically tested as researching the potential correlation between the instrument against all determinants for employment and wages is infeasible. In the absence of statistical evidence, we find it reasonable to assume that exposure to robots in the US will have no direct effect on employment and wages in Europe.

Lastly, the instrument must satisfy the independence assumption. In order to satisfy this assumption, one would ideally conduct a random experiment where exposure to robots is randomly assigned. However, since such an experiment is infeasible, we cannot completely rule out the possibility that the instrument is related to the omitted variables.

6.0 Results

In this section, we will present our empirical results and discuss our main findings based on our TSLS estimations. The discussion will be provided in light of previous studies. Full versions of the empirical results are presented in in Table 2-5 in the Appendix.

First, we document the increased use of industrial robots across countries and industries and provide a general discussion with respect to the rapid changes in robot usage and future developments. Next, we will derive the results of robot exposure on employment and wages. The different employment and wage specifications suggests that depending on gender, age and education level, a higher robot density will impact both wages and employment either by a productivity effect or by a displacement effect. Furthermore, there are significant differences in terms of the strength of the effect. The variation between the demographic groups will therefore be discussed. Hence, we will evaluate the economic importance of robot exposure by looking at how they impact the labour market. Further, we will discuss how these findings fit in light of previous studies and with respect to our pre-empirical intuition.

Our estimates imply that industrial robots increased the employment rate by a coefficient of 0.7-0.8, and increased wages by 0.19-0.13 per additional robot – however the wage results are only sporadically significant. The coefficient values refer to a percentage point change and indicates a dominating productivity effect for both the employment level and for the wage level. These numbers are quite small, and somewhat similar to the results found by Dauth et al. (2018) in German labour markets.

As we, quite unrealistically, look at Europe as a set of countries that are closed economies without any interaction – these numbers give us the aggregate effect of robots on European employment and wages. We have instead chosen to focus on the effects that might occur given different sub-groups of the economy such as different age groups, educational lIn practice, if the use of robots in one country becomes more intensive, this would reduce costs across Europe, and thus trigger some increase in both employment and wage levels in the other countries.

Our model, by not including trade between countries, might therefore imply somewhat larger effects on employment and wages than if we would have included trade, and should therefore be interpreted with some caution.evels and differences in gender. We have found that employees with a high level of education seems to benefit more from robot exposure, while it contributes negatively to the employment level of the lowest education group when it comes to employment.

However, we cannot rule out the possibility that the implementation (or use) of robots coincide with the adoption of other labour-saving technologies since we only partially control for this using an ICT-control (column 4). Hence, most of our results will have to be regarded as the joint impact of these technologies. As a matter of fact, the use of robots may in fact prompt the use of other neighbouring technologies that might also reduce the need for labour. Hence, a possible interpretation of our results may be that they measure the effect of industrial robots and other technological changes that are triggered by the adoption of industrial robots. Our results imply that the introduction of one more robot increase the employment level and the wage, which is somewhat supported by case studies and reports on the relative productivity of robots (Chiacchio et al., 2018; Dauth et al., 2018; Ford, 2015; Masayuki, 2017; McAfee, 2017a, 2017b).

6.1 Effect of Robot Development

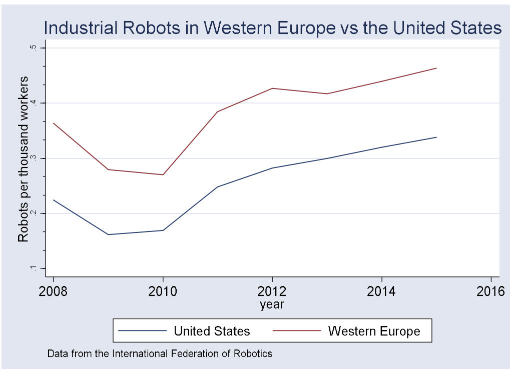

Figure 2 – All Sectors

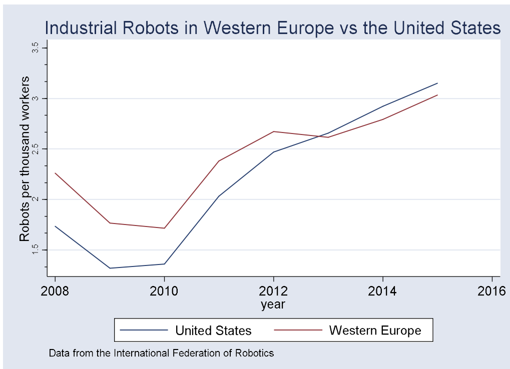

Figure 3 - Manufacturing

There are similar trend in the use of industrial robots in Europe and the US, which can be seen in the figures above. There are larger differences when we look at all sectors than the manufacturing sector. The growth in the exposure to robots is higher in other regions in the world, such as Asia, and it might be that this these countries will become leading with robot adoption in the coming years. As for now, part of our sample is defined by McKinsey & Company (2017a) as the "digital front-runners" in Europe. These countries are the Scandinavian countries Denmark, Norway and Sweden and their robot exposure can be seen in Figure 4 below. However, these figures seem to be converging, something that might be explained by the findings of Graetz and Michaels (2015) that industrial robots have diminishing marginal gains from increased use of robots and that this suggest that increasing robot exposure is not a panacea for growth.

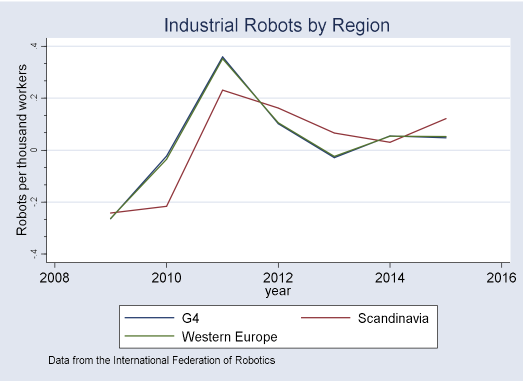

Figure 4 – Robot Exposure by Region

The report by McKinsey & Company (2017a) finds that automation and Artificial Intelligence (AI) increases both the creation of jobs and productivity. However, for employees and employers, the type of jobs are also going to face a significant shift. Transitioning into a new type of economy requires flexible training programs in order to facilitate a socially responsible transition. This might be evidence that employees with higher educational levels are more adaptable and able to attain new knowledge, something that might make them complementary to robots. Firms such as AT&T are continously retraining their employees in order to meet the rapidly shifting technology demands (Donovan, 2016).

Another interesting thing to point out is that according to IFR (2017), 99% of all robots that are installed in the core European countries are in the manufacturing sector, something that might partially explain how European manufacturers are able to successfully compete against other global actors. As stated earlier, the growth in adoption of new technologies is higher in other regions than Europe, and hence this might change the impacts on both employment and wages in the future. In the following sections, we will discuss our findings for the period between 2008-2015.

6.2 Quantitative Magnitudes

The implications for our estimates for employment and wages – meaning the implications of exposure to robots are straightforward to compute from our estimates. The effects found are quite significant for some demographic groups, however not implausible, and in line with the results found in previous studies such as (Acemoglu & Restrepo, 2017a) and (Graetz & Michaels, 2018). Our estimates include both the direct effects of robots on employment and wages and any indirect spillover effects that could arise due to a subsequent decline in local demand. We will therefore not be able to differ between the local and the aggregate effects on employment and wages in the response to robot exposure.

A relevant computation of the aggregate implications of robot exposure should account for trade between countries and regions. This is because countries that are more exposed to robots will export more of their cheaply produced products, something that might indirectly create employment in other industries in the rest of the country and/or region. Hence, as we focus our analysis on the manufacturing sector, it might be that some of the effects are offset by increases in employment and/or wages in other sectors of the economy.

6.3 Employment

Table 2 presents our main results for employment. Our outcome variable is the change in employment between 2008-2015. In addition to affecting employment, robots are also likely to affect the composition of employees. It might therefore be the case that some of the workers in our sample shift their employment into another sector of the economy.

	(1) Pooled OLS	(2) Fixed effects	(3) 2SLS	(4) ICT	(5) GMO	(6) GMO ICT
	First-stage for exposure to robots in Europe.					
Exposure to robots from 2008 to 2015			0.5785**** (0.0193)	0.5485**** (0.0235)	0.5093**** (0.0278)	0.6626**** (0.0292)
F-statistic			75.64	97.26	64.13	77.06
Observations			1008	1008	1008	1008
	Aggregate results					
Exposure to robots from 2008 to 2015	0.0280* (0.0162)	0.0271* (0.0153)	0.0843*** (0.0248)	0.0721** (0.0247)	0.0837** (0.0415)	0.0710**** (0.0347)
Observations	882	882	1008	1008	1008	1008
	Sub Group: Men					
Exposure to robots from 2008 to 2015	0.0235 (0.0154)	0.0226 (0.0144)	0.0549** (0.0269)	0.0752*** (0.0275)	0.0780**** (0.0231)	0.0789*** (0.0282)
Observations	819	819	504	504	504	504
	Sub Group: Women					
Exposure to robots from 2008 to 2015	0.0280* (0.0161)	0.0271* (0.0151)	0.110*** (0.0394)	0.0817*** (0.0293)	0.0833**** (0.0246)	0.0841*** (0.0301)
Observations	819	819	504	504	504	504
	Sub Group: 15-29					
Exposure to robots from 2008 to 2015	0.0288* (0.0163)	0.0279* (0.0155)	-0.0863** (0.0424)	0.0841*** (0.0293)	0.0848**** (0.0240)	0.0887*** (0.0303)
Observations	798	798	912	912	912	912
	Sub Group: 30-54					
Exposure to robots from 2008 to 2015	0.0229 (0.0151)	0.0211 (0.0139)	-0.131**** (0.0362)	0.0262 (0.0291)	0.0552** (0.0239)	0.0258 (0.0301)
Observations	798	798	912	912	912	912
	Sub Group: 55+					
Exposure to robots from 2008 to 2015	0.0234 (0.0153)	0.0232 (0.0143)	0.465**** (0.0444)	0.121**** (0.0288)	0.100**** (0.0236)	0.129**** (0.0298)
Observations	798	798	912	912	912	912
	Sub group: High Education					
Exposure to robots from 2008 to 2015	0.0248 (0.0158)	0.0249* (0.0148)	0.548**** (0.0431)	0.128**** (0.0291)	0.104**** (0.0239)	0.136**** (0.0301)
Observations	798	798	912	912	912	912
	Sub group: Medium Education					
Exposure to robots from 2008 to 2015	0.0248 (0.0154)	0.0241* (0.0144)	0.0751** (0.0296)	0.0967**** (0.0285)	0.0889**** (0.0234)	0.103**** (0.0295)
Observations	798	798	912	912	912	912
	Sub group: Low Education					
Exposure to robots from 2008 to 2015	0.0255 (0.0157)	0.0232 (0.0145)	-0.376**** (0.0455)	0.00694 (0.0295)	0.0473* (0.0243)	0.00509 (0.0306)
Observations	798	798	912	912	912	912
Controls						
ICT				✓		✓
GMO					✓	✓

Table 2 - Estimates of Employment by gender, age and education in Europe.

Column 3 refers to the IV results with the instrument as described in section 4.4.3 while column 4-6 refers to the controls discussed in section 4.4.4 and 4.4.5.

In the aggregate results displayed in row 2, we see that the total impact of one additional robot per thousand workers is positive and significant with a coefficient value of 0.08, indicating a dominating productivity effect. This is consistent with the study of Muro and Andes (2015), who found that although manufacturing jobs have been declining over several years Brooking Institution analysts report that countries that invested more in robots lost fewer manufacturing jobs than those that did not.

An interesting finding is that when using all industries instead of manufacturing, the coefficient value is 0.01 as opposed to 0.08. This could be due to the fact that the manufacturing sector is more influenced by robots, and given that this has been true since 1993, they might have more successfully adapted to these changes than the rest of the economy. As seen in previous industrial revolutions, there has been a tendency to move from the displacement effect, which was also found to dominate by Acemoglu and Restrepo (2017a); Chiacchio et al. (2018) as they examined the period from 1993-2007, into a productivity effect which seems to dominate in our sample period from 2008-2015.

In row 3-10, we control for differences in demographics. This offers an understanding of the dynamics underpinning the aggregate robot exposure effect on the labour market. Although the productivity effect is dominating on an aggregate level we see that this is not necessarily the case across all demographic specifications.

In the following sections, we focus on exploring the effects on different sub-groups.

6.3.1 Gender effects

	Sub Group: Men					
Exposure to robots from 2008 to 2015	0.0235 (0.0154)	0.0226 (0.0144)	0.0549** (0.0269)	0.0752*** (0.0275)	0.0780**** (0.0231)	0.0789*** (0.0282)
Observations	819	819	504	504	504	504
	Sub Group: Women					
Exposure to robots from 2008 to 2015	0.0280* (0.0161)	0.0271* (0.0151)	0.110*** (0.0394)	0.0817*** (0.0293)	0.0833**** (0.0246)	0.0841*** (0.0301)
Observations	819	819	504	504	504	504

Table 2a - Estimates of Employment by gender in Europe.

Qualitatively we experience similar results for men and women, with significant positive results for both groups. In terms of quantitative results, there is differences in the strength of the effect. Our results indicate that men are less affected than women, with a female coefficient value of 0.11 and a male coefficient value of 0.05. However, both gender specifications fail to provide a robust positive impact. Hence, these results should only be regarded as suggestive.

These results both fit and contradict previous studies. Our findings fit well with Acemoglu and Restrepo (2017a), where they found that men are 1.5-2 times more negatively affected. However, it contradicts the findings in Lawrence et al. (2017) who found that a greater share of jobs held by women was susceptible to automation, as it is more likely that female workers hold low-skilled and automatable occupations.

Regarding our own pre-empirical belief, we were ambivalent in what we expected. Given the assumption argued by Lawrence et al. (2017) that female workers are generally more prone to hold low-skilled occupations that in theory should be more susceptible to automation we should expect that women would be more negatively affected than men, or less positively affected. In addition, female workers are more present in sectors where investments in technology are lower, such as retail and care.

6.3.2 Age effects

	Sub Group: 15-29					
Exposure to robots from 2008 to 2015	0.0288^{*} (0.0163)	0.0279^{*} (0.0155)	-0.0863^{**} (0.0424)	0.0841^{***} (0.0293)	0.0848^{****} (0.0240)	0.0887^{***} (0.0303)
Observations	798	798	912	912	912	912
	Sub Group: 30-54					
Exposure to robots from 2008 to 2015	0.0229 (0.0151)	0.0211 (0.0139)	-0.131^{****} (0.0362)	0.0262 (0.0291)	0.0552^{**} (0.0239)	0.0258 (0.0301)
Observations	798	798	912	912	912	912
	Sub Group: 55+					
Exposure to robots from 2008 to 2015	0.0234 (0.0153)	0.0232 (0.0143)	0.465^{****} (0.0444)	0.121^{****} (0.0288)	0.100^{****} (0.0236)	0.129^{****} (0.0298)
Observations	798	798	912	912	912	912

Table 2b - Estimates of Employment by age in Europe.

Results for the different age groups helps us understand the dynamics of the competition between robots and workers. We see similar results for the two youngest age groups – negative and statistically significant with coefficient values at -0.09 and -0.10 respectively. The oldest age demographic however, experience positive and statistically significant effects with a robust coefficient value of 0.46.

These findings are consistent with previous studies (Chiacchio et al., 2018), and can be justified by evidence from the German labour market from Dauth et al. (2018), who indicated that firms generates less jobs that can be filled by young workers, and rather employ incumbent workers in different positions after new industrial robots are installed. In addition, the type of work that is traditionally replaced by robots tend to be physically demanding and therefore will typically not affect the older workforce. The youngest workers will also consist of more low-skilled labour since they naturally would not have been able to attain education yet. Hence, this would make them further susceptible for automation.

6.3.3 Education effects

	Sub group: High Education					
Exposure to robots from 2008 to 2015	0.0248 (0.0158)	0.0249* (0.0148)	0.548**** (0.0431)	0.128**** (0.0291)	0.104**** (0.0239)	0.136**** (0.0301)
Observations	798	798	912	912	912	912
	Sub group: Medium Education					
Exposure to robots from 2008 to 2015	0.0248 (0.0154)	0.0241* (0.0144)	0.0751** (0.0296)	0.0967**** (0.0285)	0.0889**** (0.0234)	0.103**** (0.0295)
Observations	798	798	912	912	912	912
	Sub group: Low Education					
Exposure to robots from 2008 to 2015	0.0255 (0.0157)	0.0232 (0.0145)	-0.376**** (0.0455)	0.00694 (0.0295)	0.0473* (0.0243)	0.00509 (0.0306)
Observations	798	798	912	912	912	912

Table 2c - Estimates of Employment by education in Europe.

Our estimations indicate significant positive effects for workers with high level of educational attainment. We find small and marginally significant positive effects on workers with medium education, while there is a significant negative effects for the group with the lowest level of education. The coefficient values are 0.55, 0.01 and -0.38 for high, medium and low respectively. The TSLS estimation are robust for high and low group.

Acemoglu and Restrepo (2017a) found negative effects on employment for workers with low levels of education. Additionally, they found that medium educated workers had a small and marginally significant negative effect. This is all in line with our findings. However, they found no effect on highly educated workers which is surprising given our results.

Goos and Manning (2007) and Goos et al. (2009) find that both for Europe and the UK, there is a shift away from workers who conduct routine tasks. As these are tasks generally performed by middle-skilled workers, one would expect the medium educated work force to be the most affected when it comes to employment. One possible explanation could be the decline in the quality-adjusted prices (Chiacchio et al., 2018), and that the low educated workers are now more likely to be substituted by capital than they were with previous prices. In addition, it could be that robots are not so complementary to these well-defined groups of workers within the manufacturing sector, and as such, the effects are greater than for the economy as a whole. Further, it might be that robots have counterbalancing effects for employment within manufacturing, as different occupations are affected differently by automation. Therefore, it could be that workers are shifted from i.e. the automotive sector and into another sector within manufacturing.

The rationale behind why the highly educated demographic is most positively affected could be that occupations that are associated with high levels of education, might be more complementary to automation than occupations associated with lower levels of occupations. This is in line with the findings from Denmark, where McKinsey & Company (2017b) found that workers with low educational levels are active in occupations that face a 52% automation potential, much larger than the automation potential of 24% for those workers with higher levels of education.

Some of the least automatable jobs are the jobs consisting of novel situations, something that puts a limit to the tasks that machines can automate (Goldbloom, 2017). One example of how humans can exploit this is the invention of the microwave, which was done when Percy Spencer noticed how a chocolate bar reacted to the magnetron from a radar – something a machine would not be able to do. Smaller examples of this type of creativity happen on a frequent basis and is something humans are able to use to their advantage. Creating business strategies and marketing campaigns are tasks that, at least for now, is more suitable for humans as they entail finding gaps in the market (Goldbloom, 2017).

Susskind (2018) claimed that as robots and machines become more capable and able to perform various tasks, both routine and non-routine, they strengthen the force of machine substitution and weaken the force of machine complementarity – and that at some point this balance would favour the machines as opposed to human beings. Contrary to this, our findings suggest that as robots and machines become more capable and versatile, the highly educated workers seem to adapt to these changes more easily.

	(1) Pooled OLS	(2) Fixed effects	(3) IV	(4) ICT	(5) GMO	(6) GMO ICT
	First-stage for exposure to robots in Europe.					
Exposure to robots from 2008 to 2015			0.6050**** (0.0290)	0.1005 (0.1828)	0.6458**** (0.1933)	0.6626**** (0.0292)
F-statistic			90.51	91.07	61.16	69.74
Observations			1008	1008	1008	1008
	Aggregate results					
Exposure to robots from 2008 to 2015	0.1046**** (0.0202)	0.1070**** (0.0120)	0.194* (0.0293)	0.183 (0.0298)	0.147* (0.0363)	0.130* (0.0363)
Observations	882	882	1008	1008	1008	1008
	Sub Group: Men					
Exposure to robots from 2008 to 2015	0.0955**** (0.0195)	0.0983**** (0.0194)	0.171* (0.0278)	0.167 (0.0285)	0.151 (0.0347)	0.142** (0.0358)
Observations	819	819	819	819	819	819
	Sub Group: Women					
Exposure to robots from 2008 to 2015	0.1001**** (0.0202)	0.1027**** (0.0199)	0.172* (0.0286)	0.170 (0.0293)	0.151 (0.0356)	0.146* (0.0369)
Observations	819	819	819	819	819	819
	Sub Group: 15-29					
Exposure to robots from 2008 to 2015	0.0975*** (0.0205)	0.1005*** (0.0204)	0.172** (0.0292)	0.171 (0.0299)	0.143 (0.0363)	0.136* (0.0381)
Observations	798	798	798	798	798	798
	Sub Group: 30-54					
Exposure to robots from 2008 to 2015	0.0951*** (0.0194)	0.0970*** (0.0188)	0.156** (0.0269)	0.157** (0.0275)	0.158* (0.0336)	0.159** (0.0353)
Observations	798	798	798	798	798	798
	Sub Group: 55+					
Exposure to robots from 2008 to 2015	0.0939*** (0.0194)	0.0974*** (0.0192)	0.162*** (0.0274)	0.162* (0.0280)	0.156* (0.0342)	0.155** (0.0359)
Observations	798	798	798	798	798	798
	Sub group: High Education					
Exposure to robots from 2008 to 2015	0.0958*** (0.0197)	0.0100*** (0.0195)	0.160*** (0.0278)	0.162* (0.0285)	0.150* (0.0347)	0.154** (0.0365)
Observations	798	798	798	798	798	798
	Sub group: Medium Education					
Exposure to robots from 2008 to 2015	0.0963*** (0.0195)	0.0100*** (0.0193)	0.172** (0.0277)	0.167 (0.0283)	0.164 (0.0346)	0.153 (0.0362)
Observations	798	798	798	798	798	798
	Sub group: Low Education					
Exposure to robots from 2008 to 2015	0.0943*** (0.0201)	0.0957*** (0.0196)	0.159*** (0.0280)	0.160** (0.0287)	0.144** (0.0349)	0.144* (0.0367)
Observations	798	798	798	798	798	798
Controls						
ICT				✓		✓
GMO					✓	✓

Table 3 - Estimates of Wage by gender, age and education in Europe.

6.4 Wages

Table 3 presents our main results for wages. Similarly, to the results on employment, wages might only change in the manufacturing sector, and not for the economy as a whole due to changes in the composition of employment. Our outcome variable is the change in wages between 2008-2015. Our results indicate that the effects on wages is quite comparable across all demographic specifications. The TSLS aggregate results displayed in row 2, indicates a positive marginally significant result of one robot additional robot per thousand workers with coefficient value of 0.194.

As we attempt to disentangle the effects into demographic groups, the results fail to point to any considerable differences in effects in terms of gender, age or education. Thus, we are less confident to conclude the wage effect, even if most results points to a small positive and marginally significant effect. It appears to be difficult to identify a clear relationship between robot exposure and wages when looking at our sub-groups. Hence, we must therefore conclude that the few scattered significant results using controls can only be regarded as suggestive evidence that need to be further tested.

6.4.1 Gender effects

	Sub Group: Men					
Exposure to robots from 2008 to 2015	0.0955**** (0.0195)	0.0983**** (0.0194)	0.171* (0.0278)	0.167 (0.0285)	0.151 (0.0347)	0.142** (0.0358)
Observations	819	819	819	819	819	819
	Sub Group: Women					
Exposure to robots from 2008 to 2015	0.1001**** (0.0202)	0.1027**** (0.0199)	0.172* (0.0286)	0.170 (0.0293)	0.151 (0.0356)	0.146* (0.0369)
Observations	819	819	819	819	819	819

Table 3a - Estimates of Wage by gender in Europe.

These results both fit and contradict previous studies. Our findings fit well with earlier studies such as Acemoglu and Restrepo (2017a), where they found that wage effects are of comparable size for the two gender groups. However, it contradicts the findings in Lawrence et al. (2017) who found that a greater share of jobs held by women was susceptible to automation, as it is more likely that female workers hold low-skilled and automatable occupations.

Regarding our own pre-empirical belief, we were ambivalent in what we expected. Black and Spitz-Oener (2010) explored an approach where they analysed the changes in the gender gap by how work for men and women has changed in recent time. They found that women have increased their non-routine, analytic and interactive tasks – and that this decline in routine tasks was in part driven by technological change. These findings are helpful to our results as they might help to explain why women's wages seem to be slightly more positively affected than the wages for men. Another study looking at the gender equality is the one by Mulligan and Rubinstein (2018), which show that able women are pulling into the labour market. They argue that the relative wage equality between genders coincide with an increase in the inequality within gender groups. Another interesting fact that might explain why women are more affected by men is that according to Autor (2010), the male/female gap in college attainment went from positive 8 to negative 8 percentage points.

6.4.2 Age effects

	Sub Group: 15-29					
Exposure to robots from 2008 to 2015	0.0975*** (0.0205)	0.1005*** (0.0204)	0.172** (0.0292)	0.171 (0.0299)	0.143 (0.0363)	0.136* (0.0381)
Observations	798	798	798	798	798	798
	Sub Group: 30-54					
Exposure to robots from 2008 to 2015	0.0951*** (0.0194)	0.0970*** (0.0188)	0.156** (0.0269)	0.157** (0.0275)	0.158* (0.0336)	0.159** (0.0353)
Observations	798	798	798	798	798	798
	Sub Group: 55+					
Exposure to robots from 2008 to 2015	0.0939*** (0.0194)	0.0974*** (0.0192)	0.162*** (0.0274)	0.162* (0.0280)	0.156* (0.0342)	0.155** (0.0359)
Observations	798	798	798	798	798	798

Table 3b - Estimates of Wage by gender in Europe.

We find that the two outlying groups of employees are most positively impacted by robot exposure, whereas the middle group is the least affected. These findings are consistent with previous studies Acemoglu and Restrepo (2017b), who find that countries undergoing more pronounced demographic changes are more rapidly adopting automation technologies. In addition, they find that countries with a larger group of old employees are growing at a faster pace, something that might explain how a group thought to be less agile in terms of new technology are experiencing an outweighing productivity effect. The findings contradict those of Schloegel (2018), who found that middle aged employees are the ones favoured by software development.

In addition, Bartel and Sicherman (2015) found that production workers in manufacturing industries with higher rates of technological change were more likely to receive formal company training – something that might explain why wages increase for the oldest age group.

These findings are somewhat inconsistent with our pre-empirical perceptions, as the middle aged group is the least affected. One explanation could be that younger employees have an advantage in being more agile in their response to robots, whereas robots are complementing the older employees.

6.4.3 Education effects

	Sub group: High Education					
Exposure to robots from 2008 to 2015	0.0958*** (0.0197)	0.0100*** (0.0195)	0.160*** (0.0278)	0.162* (0.0285)	0.150* (0.0347)	0.154** (0.0365)
Observations	798	798	798	798	798	798
	Sub group: Medium Education					
Exposure to robots from 2008 to 2015	0.0963*** (0.0195)	0.0100*** (0.0193)	0.172** (0.0277)	0.167 (0.0283)	0.164 (0.0346)	0.153 (0.0362)
Observations	798	798	798	798	798	798
	Sub group: Low Education					
Exposure to robots from 2008 to 2015	0.0943*** (0.0201)	0.0957*** (0.0196)	0.159*** (0.0280)	0.160** (0.0287)	0.144** (0.0349)	0.144* (0.0367)
Observations	798	798	798	798	798	798

Table 3c - Estimates of Wage by gender in Europe.

We found that the least educated are least affected, but that the two groups with higher educational levels are only marginally more positive. Our findings are in line with the findings of Valletta (2016), who found that the wage gap between educational groups have progressively slowed due to a decrease in the demand for advanced cognitive skills and a shift away from middle-skilled occupations due to technological change. However, McKinsey & Company (2017b) found that education length is correlated with the task performed, something that means that employees with low levels of education spend more time on tasks that are susceptible to automation. This slightly contradicts our findings for the effect of robot exposure on wages, something that might indicate differences between the aggregate European and the local Danish labour markets.

In addition, Acemoglu (2002) wrote that: "If the rate of utilization of technology is accelerating, or if the technology gap is growing, the return to education will rise relative to other inputs". This shows that previous studies on the return of human capital is positive in regards to wages, hence it is somewhat surprising that the groups have fairly similar effects on wages from robot exposure.

In the first half of the 1990s, there was an enormous influx of highly educated employees from the Soviet Unions, something that increased the Israeli population by 12 percent. The relative wages of educated employees would, given a theory with exogenous technology, face a large decline. However, in practice these education premiums on wages did not fall (Friedberg, 2001). In our sample period, the number of highly educated employees have grown for most of the countries. This can i.e. be seen in Figure 5, which shows the percentage of the working population that have a high level of education. We see that despite growing numbers of highly educated employees in Europe, the wages increase with robot exposure.

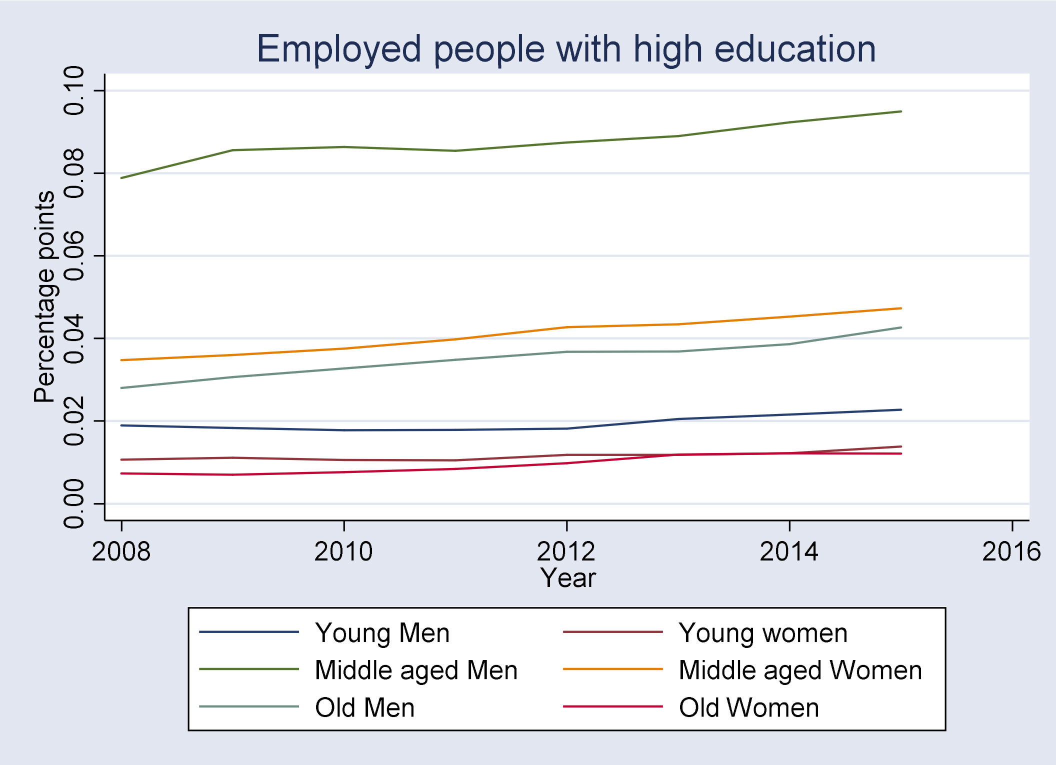

Figure 5 – Percentage of employees with High Education

7.0 Conclusion

Automation, robots and artificial intelligence (AI) are playing a greater role than ever before in many advanced economies and are increasingly affecting labour markets. It is anticipated that these technologies will become even more common and affect even more jobs in the coming years. Consequently, we see that there are increasing concerns about how this will affect labour markets. Some researchers say that around 50% of all jobs will disappear in the next 30 years, while others say that wages will stagnate. Despite this, little research is done on the effects of these new technologies and in particular; how they affect employment and wages.

In this paper we have therefore attempted to assess the impact of industrial robots on employment and wages in Europe in the period 2008-2015. The assessment is done by applying a simplification of the model used by (Acemoglu & Restrepo, 2017a). In the model, without trade between labour markets, robots may either have a positive, negative or insignificant effect on employment and wages. A positive impact would stem from a productivity effect, while a negative effect would be due to a displacement of employees by robots. We regress the change in employment and wages on the exposure to robots in Europe's aggregate labour market to assess the different labour market effects. The exposure to robots is defined as the sum of robots per thousand workers.

Our empirical work attempts to exploit the exogenous components of the exposure to robots, coming from the technological frontier (Acemoglu & Restrepo, 2017a). This enables us to separate the effect of the robot exposure from the potentially endogenous trends reflecting other industry-level developments that might be correlated with robot usage in Europe. Using this methodology, we estimate robust positive effects of robot exposure on employment for most of the demographic groups. In addition, we see some indications that suggest a positive effect on all sub-groups when it comes to wage. Our estimates imply that each additional robots per thousand workers would increase the employment to population ratio with a coefficient of 0.07-0.08 and decrease wages by with a coefficient of 0.13-0.19. Hence, demonstrating a dominating productivity effect within both employment and wages.

However, as the number of industrial robots are expected to increase in the coming decades (Brynjolfsson, 2017; Brynjolfsson & McAfee, 2014), these effects may become even larger in the future. Sirkin, Zinser, and Rose (2015) offers two scenarios when it comes to the spread of robots in the next two decades – where the most aggressive scenario predicts a quadrupling of industrial robots and even their more cautious scenario predicts almost 300% as many robots in 2025 as that of 2015. However, some of the responses of wages and employment might be different once the number of robots exceeds a critical threshold and some of the effects might only slowly emerge (Acemoglu & Restrepo, 2016).

Previous industrial revolutions have shown that even though a displacement effect might dominate short-term, it is replaced by a productivity effect as soon as the markets and societies become more adapted to the change and have shown to have a positive effect on both employment and the wage.

This paper should be regarded as complementary to that of Acemoglu and Restrepo (2017a), as they looked at labour market effects across commuting zones in the US, where this paper looks at cross-country comparisons in Europe. However, we believe that our methodology's ability to estimate these labour market responses is an important step in estimating the more comprehensive analyses of the effect of robots. In addition, we believe that the positive effects that we have estimated in this paper are both interesting and somewhat surprising and hope that they can generate healthy discussions about a topic that we assume will be ever growing in importance over the coming decades. After all, the issues of labour displacement and productivity effects are good problems to have. Previously, the dominating economic question have been how to create an economic pie that is big enough for everyone to live on. The problem now seems to be how to divide the pie in such a manner that everyone gets a slice – something that might be more easily achieved with the increased focus on a highly educated workforce. In addition, the importance of a flexible workforce together with structured education in order to build further capabilities on the job will come to show as robots are becoming even more common. As technology advances and robots are capable of more tasks, there will be an increasing need for both up- and re-skilling employees.

8.0 Figures and tables

Figure 1 – The Share of Industrial Robots in Manufacturing

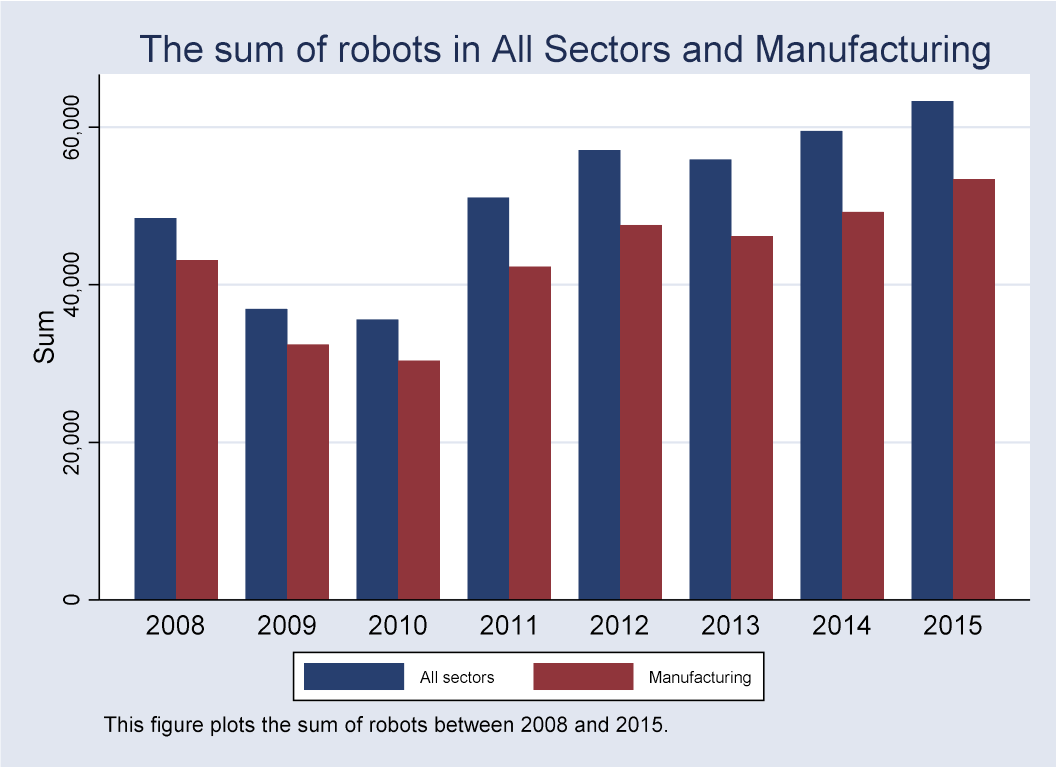

Figure 2 – Industrial Robots in Manufacturing, comparison between Europe/US.

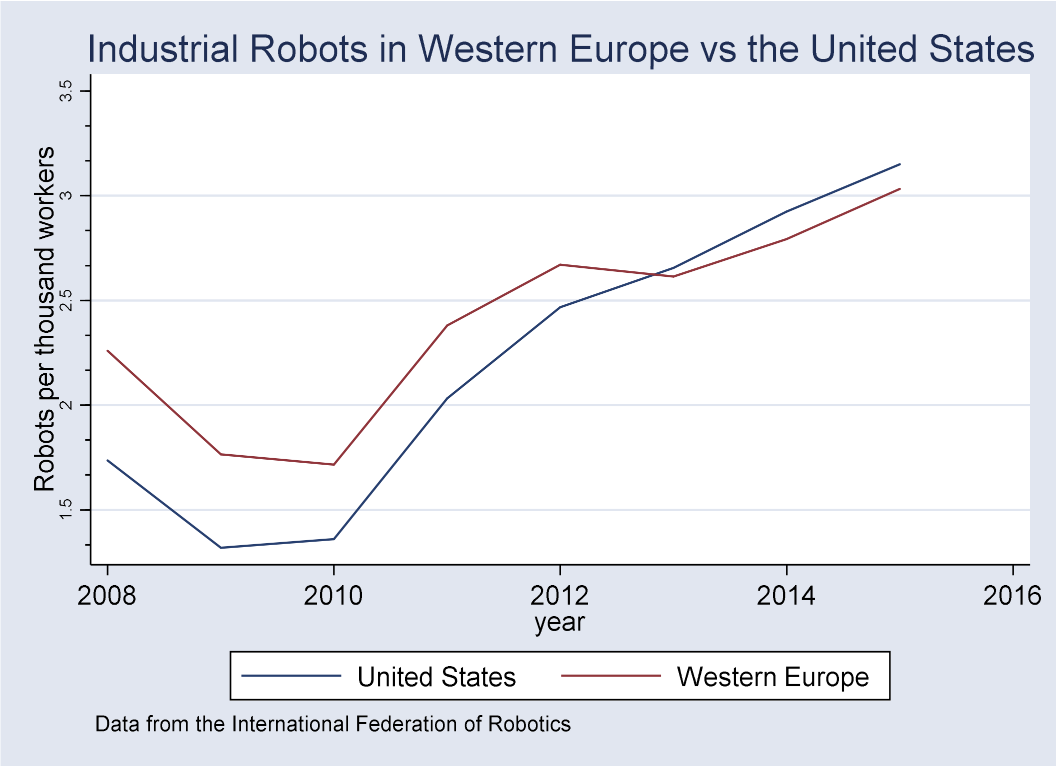

Figure 3 – Industrial Robots in all sectors, a comparison between Europe/US.

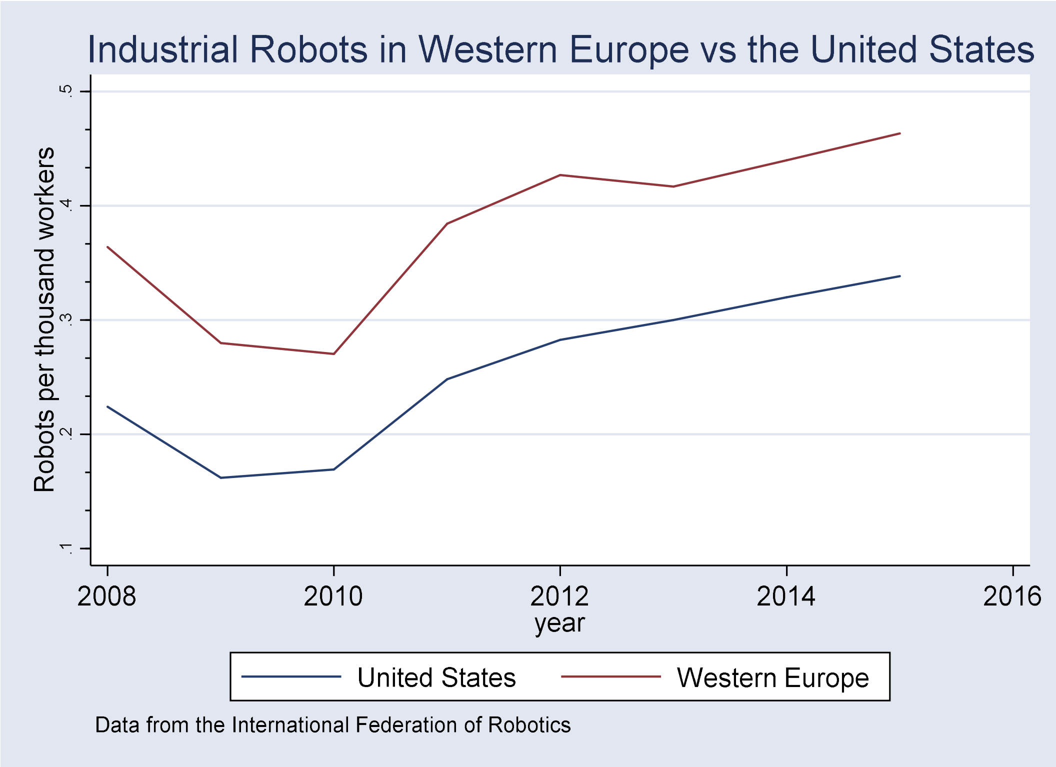

Figure 4 - Industrial Robots in Manufacturing by our 3 regions.

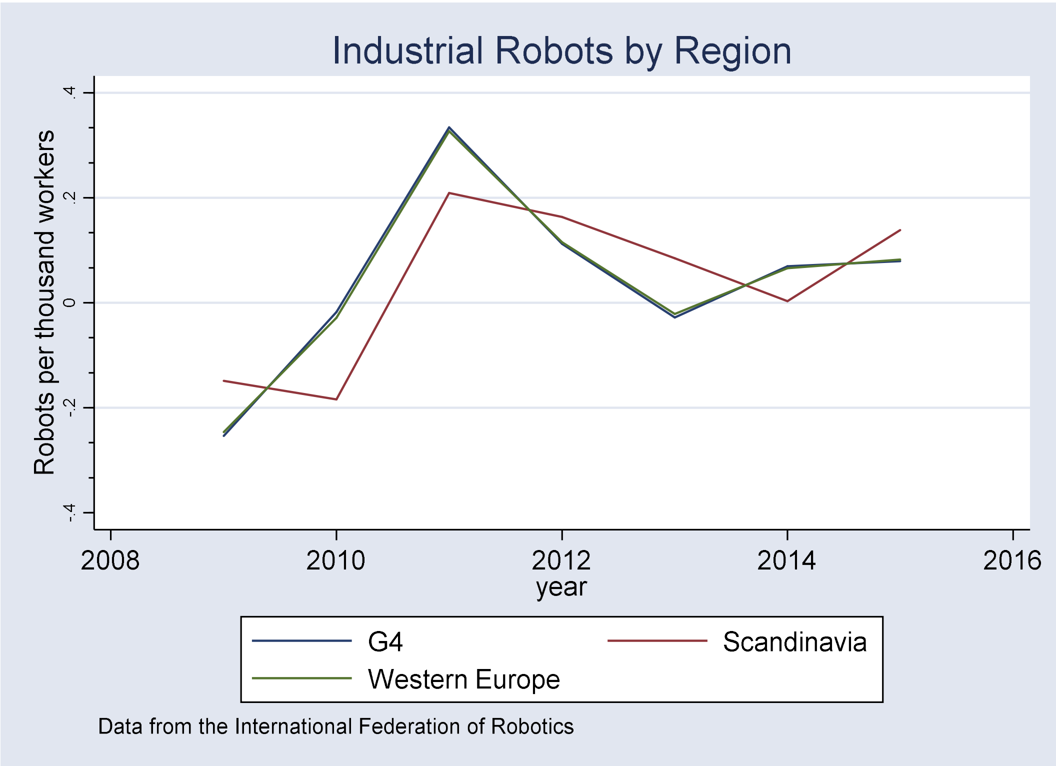

Figure 5 – Employed people in Manufacturing with a high level of education.

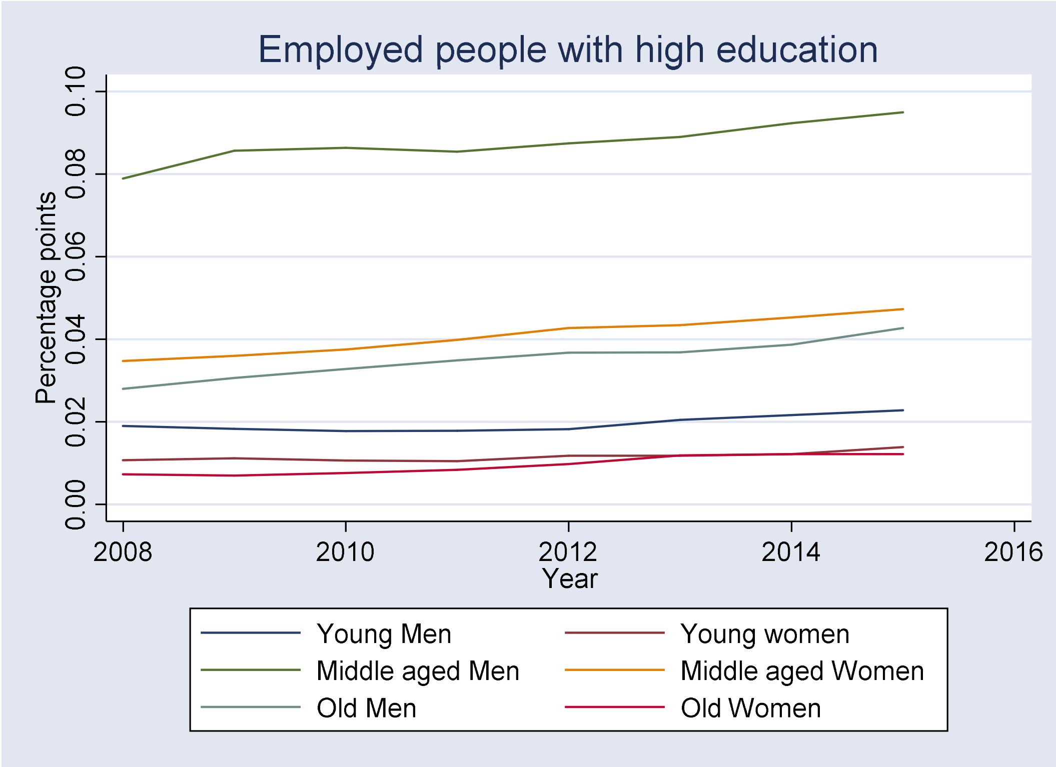

Figure 6 - Industrial Robots in Manufacturing by 4 regions.

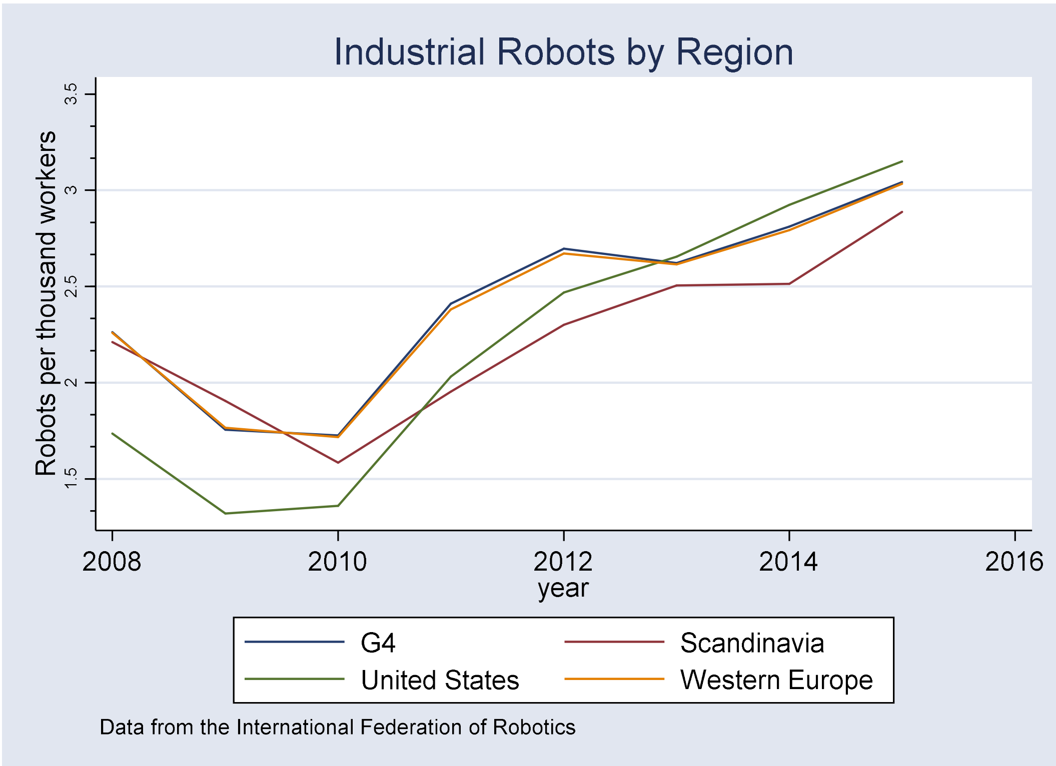

Figure 7 - Industrial Robots in Manufacturing by country.

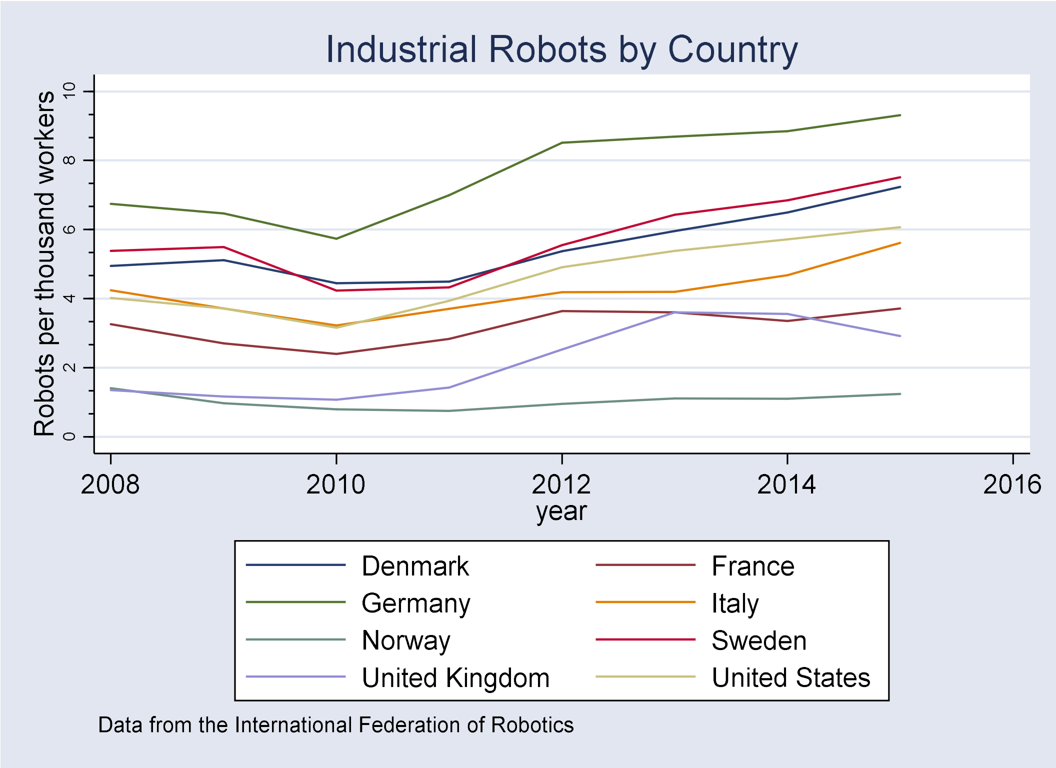

Figure 8 – Industrial Robots in all sectors separated by all 4 regions.

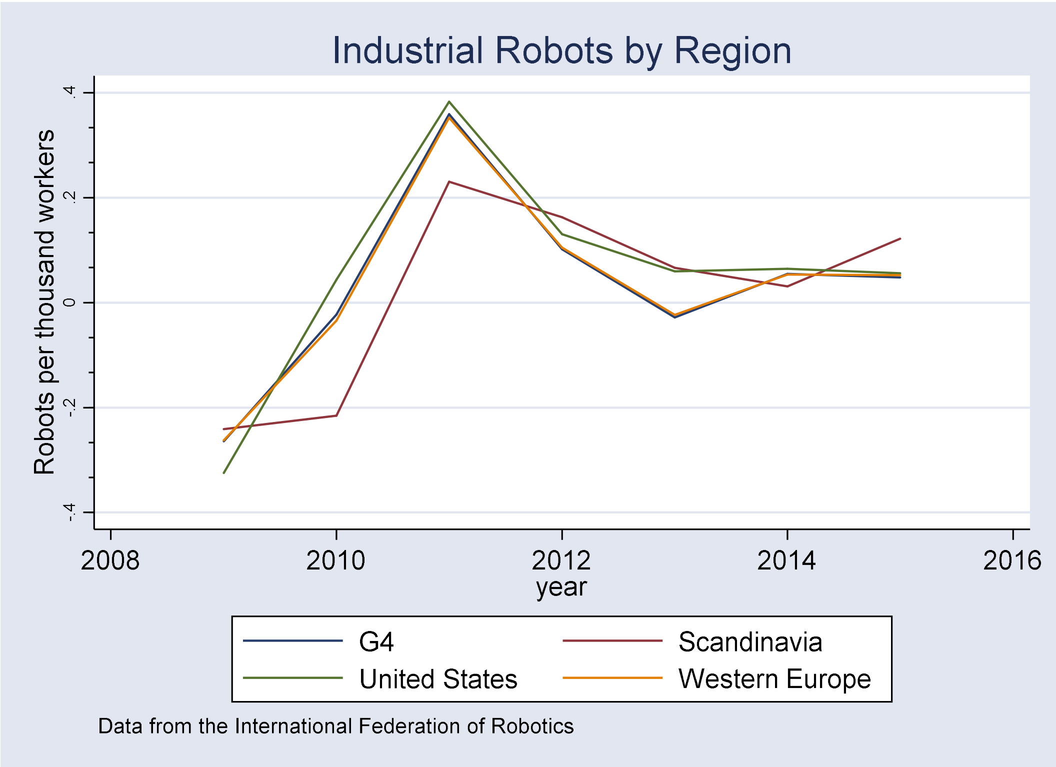

Figure 9 – Industrial Robots in all sectors, separated by our 3 regions.

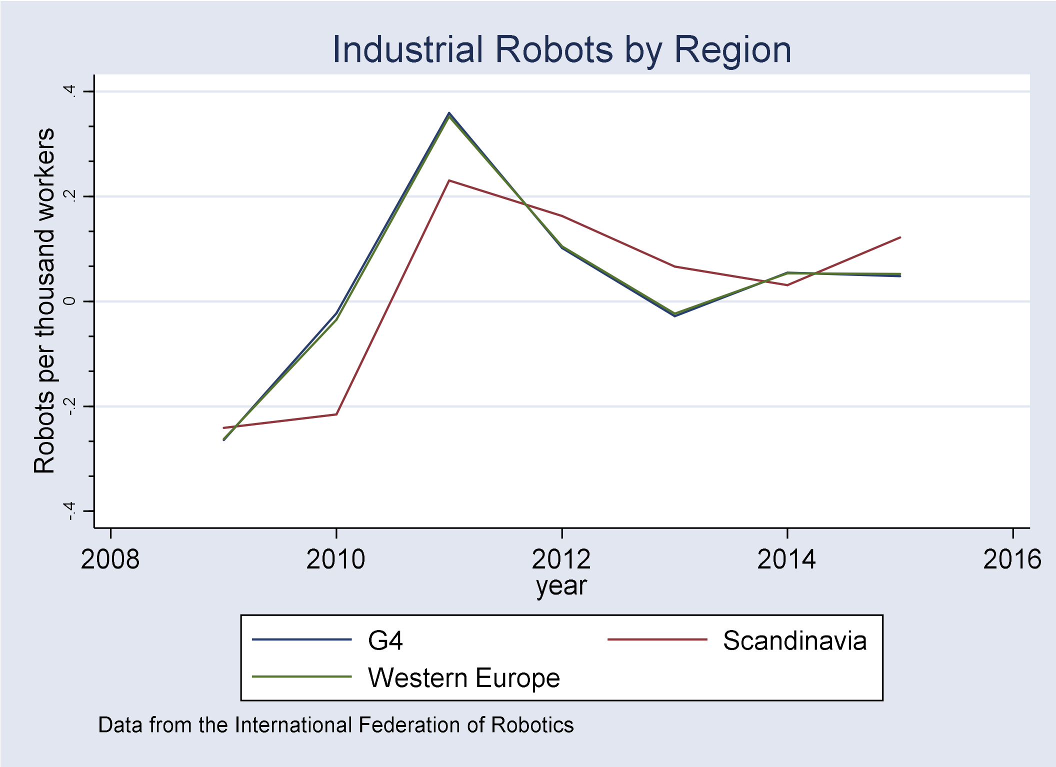

Figure 10 – Industrial robots in all sectors by country.

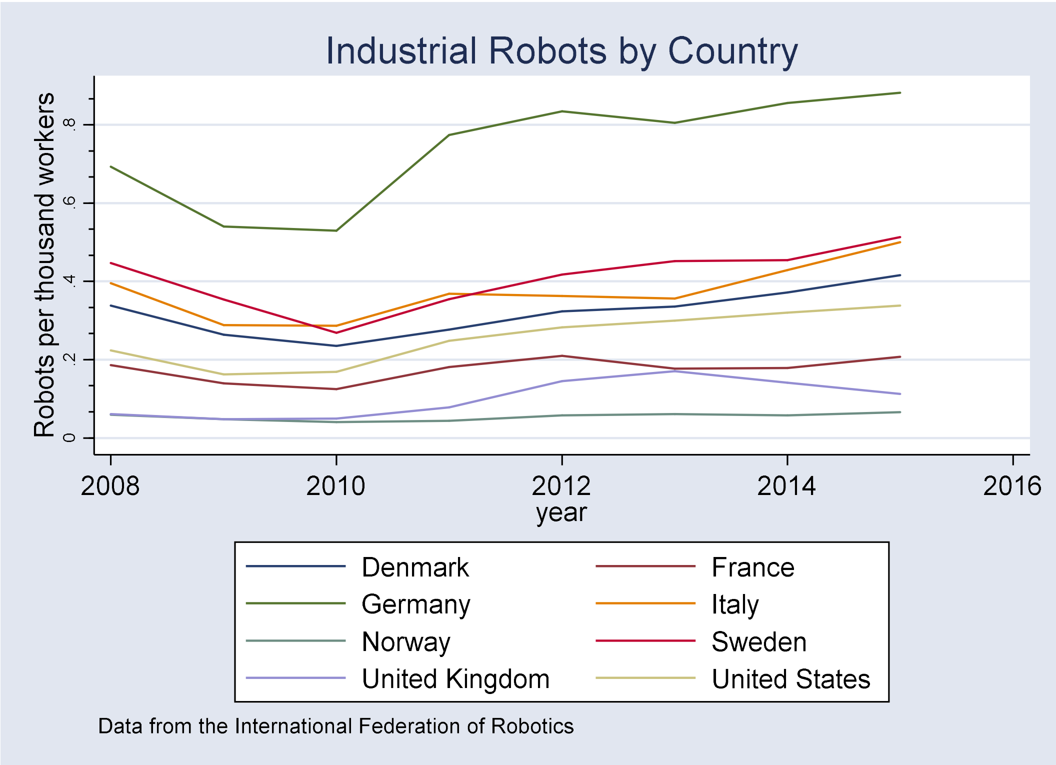

Table 1. *Descriptive Statistics*

	Mean	Standard Deviation	Min	Max
Shares of employment type in Manufacturing	0.056	(0.051)	0.001	0.282
Shares labour compensation type in Manufacturing	0.056	(0.057)	0.001	0.291
Relative change in employment	-0.016	(0.032)	-0.138	0.025
Relative change in wages	0.007	(0.033)	-0.105	0.055
Relative change in Robots	0.029	(0.170)	-0.409	0.577
Observations	1566			

Table 2. *Estimates of the impact of Robot Exposure on Employment in Europe.*

	(1) Pooled OLS	(2) Fixed effects	(3) 2SLS	(4) ICT	(5) GMO	(6) GMO ICT
	First-stage for exposure to robots in Europe.					
Exposure to robots from 2008 to 2015			0.5785**** (0.0193)	0.5485**** (0.0235)	0.5093**** (0.0278)	0.6626**** (0.0292)
F-statistic			75.64	97.26	64.13	77.06
Observations			1008	1008	1008	1008
	Aggregate results					
Exposure to robots from 2008 to 2015	0.0280* (0.0162)	0.0271* (0.0153)	0.0843*** (0.0248)	0.0721** (0.0247)	0.0837** (0.0415)	0.0710**** (0.0347)
Observations	882	882	1008	1008	1008	1008
	Sub Group: Men					
Exposure to robots from 2008 to 2015	0.0235 (0.0154)	0.0226 (0.0144)	0.0549** (0.0269)	0.0752*** (0.0275)	0.0780**** (0.0231)	0.0789*** (0.0282)
Observations	819	819	504	504	504	504
	Sub Group: Women					
Exposure to robots from 2008 to 2015	0.0280* (0.0161)	0.0271* (0.0151)	0.110*** (0.0394)	0.0817*** (0.0293)	0.0833**** (0.0246)	0.0841*** (0.0301)
Observations	819	819	504	504	504	504
	Sub Group: 15-29					
Exposure to robots from 2008 to 2015	0.0288* (0.0163)	0.0279* (0.0155)	-0.0863** (0.0424)	0.0841*** (0.0293)	0.0848**** (0.0240)	0.0887*** (0.0303)
Observations	798	798	912	912	912	912
	Sub Group: 30-54					
Exposure to robots from 2008 to 2015	0.0229 (0.0151)	0.0211 (0.0139)	-0.131**** (0.0362)	0.0262 (0.0291)	0.0552** (0.0239)	0.0258 (0.0301)
Observations	798	798	912	912	912	912
	Sub Group: 55+					
Exposure to robots from 2008 to 2015	0.0234 (0.0153)	0.0232 (0.0143)	0.465**** (0.0444)	0.121**** (0.0288)	0.100**** (0.0236)	0.129**** (0.0298)
Observations	798	798	912	912	912	912
	Sub group: High Education					
Exposure to robots from 2008 to 2015	0.0248 (0.0158)	0.0249* (0.0148)	0.548**** (0.0431)	0.128**** (0.0291)	0.104**** (0.0239)	0.136**** (0.0301)
Observations	798	798	912	912	912	912
	Sub group: Medium Education					
Exposure to robots from 2008 to 2015	0.0248 (0.0154)	0.0241* (0.0144)	0.0751** (0.0296)	0.0967**** (0.0285)	0.0889**** (0.0234)	0.103**** (0.0295)
Observations	798	798	912	912	912	912
	Sub group: Low Education					
Exposure to robots from 2008 to 2015	0.0255 (0.0157)	0.0232 (0.0145)	-0.376**** (0.0455)	0.00694 (0.0295)	0.0473* (0.0243)	0.00509 (0.0306)
Observations	798	798	912	912	912	912
Controls						
ICT				✓		✓
GMO					✓	✓

Notes: IV estimates of the impact of the exposure to robots on employment. Standard errors are given in parentheses. The coefficients with *** are significant at the 1% level, ** are significant at the 5% level and * significant at the 10% level. Column 1 is the results for our OLS specification. Column 2 is the results from our fixed effects model with within-estimator. Column 3 is the 2SLS results with no controls. Column 4 also includes a control for the share of ICT. Column 5 controls for changes in output, while columns 6 includes both controls for changes in output and the share of ICT.

Table 3. *Robust estimates of Employment by gender, age and education in Europe.*

	(1) Pooled OLS	(2) Fixed effects	(3) IV	(4) ICT	(5) GMO	(6) GMO ICT
	Aggregate results					
Exposure to robots from 2008 to 2015	0.0280* (0.0153)	0.0271* (0.0138)	0.0803*** (0.0248)	0.0798** (0.0247)	0.0837 (0.0415)	0.0710 (0.0833)
Observations	882	882	1008	1008	1008	1008
	Sub Group: Men					
Exposure to robots from 2008 to 2015	0.0235 (0.0152)	0.0226 (0.0137)	0.0549 (0.0530)	0.0752 (0.0507)	0.0780 (0.0486)	0.0789 (0.0525)
Observations	819	819	504	504	504	504
	Sub Group: Women					
Exposure to robots from 2008 to 2015	0.0280* (0.0152)	0.0271* (0.0151)	0.110 (0.0850)	0.0817 (0.0618)	0.0833 (0.0517)	0.0841 (0.0646)
Observations	819	819	504	504	504	504
	Sub Group: 15-29					
Exposure to robots from 2008 to 2015	0.0288* (0.0154)	0.0279* (0.0155)	-0.0863 (0.0774)	0.0841 (0.0539)	0.0848* (0.0498)	0.0887 (0.0563)
Observations	798	798	912	912	912	912
	Sub Group: 30-54					
Exposure to robots from 2008 to 2015	0.0229 (0.0151)	0.0211 (0.0139)	-0.131 (0.0801)	0.0262 (0.0584)	0.0552 (0.0511)	0.0258 (0.0616)
Observations	798	798	912	912	912	912
	Sub Group: 55+					
Exposure to robots from 2008 to 2015	0.0234 (0.0152)	0.0232 (0.0143)	0.465*** (0.0872)	0.121** (0.0549)	0.100** (0.0501)	0.129** (0.0575)
Observations	798	798	912	912	912	912
	Sub group: High Education					
Exposure to robots from 2008 to 2015	0.0248 (0.0153)	0.0249* (0.0148)	0.548*** (0.0761)	0.128** (0.0545)	0.104** (0.0502)	0.136** (0.0567)
Observations	798	798	912	912	912	912
	Sub group: Medium Education					
Exposure to robots from 2008 to 2015	0.0248 (0.0152)	0.0241* (0.0144)	0.0751 (0.0603)	0.0967* (0.0520)	0.0889* (0.0493)	0.103* (0.0545)
Observations	798	798	912	912	912	912
	Sub group: Low Education					
Exposure to robots from 2008 to 2015	0.0255* (0.0152)	0.0232 (0.0145)	-0.376**** (0.0830)	0.00694 (0.0589)	0.0473 (0.0514)	0.00509 (0.0620)
Observations	798	798	912	912	912	912
Controls						
ICT				✓		✓
GMO					✓	✓

Notes: Robust IV estimates of the impact of the exposure to robots on employment. Standard errors are given in parentheses. The coefficients with *** are significant at the 1% level, ** are significant at the 5% level and * significant at the 10% level. Column 4 is the baseline results with no controls. In column 2 also includes a control for the share of ICT. Column 3 controls for changes in output. Column 4 controls for changes in the labour force. Lastly, column 5 controls for both the change in output and the level of ICT.

Table 4. *Estimates of Wage by gender, age and education in Europe.*

	(1) Pooled OLS	(2) Fixed effects	(3) IV	(4) ICT	(5) GMO	(6) GMO ICT
	First-stage for exposure to robots in Europe.					
Exposure to robots from 2008 to 2015			0.6050**** (0.0290)	0.1005 (0.1828)	0.6458**** (0.1933)	0.6626**** (0.0292)
F-statistic			90.51	91.07	61.16	69.74
Observations			1008	1008	1008	1008
	Aggregate results					
Exposure to robots from 2008 to 2015	0.1046**** (0.0202)	0.1070**** (0.0120)	0.194* (0.0293)	0.183 (0.0298)	0.147* (0.0363)	0.130* (0.0363)
Observations	882	882	1008	1008	1008	1008
	Sub Group: Men					
Exposure to robots from 2008 to 2015	0.0955**** (0.0195)	0.0983**** (0.0194)	0.171* (0.0278)	0.167 (0.0285)	0.151 (0.0347)	0.142** (0.0358)
Observations	819	819	819	819	819	819
	Sub Group: Women					
Exposure to robots from 2008 to 2015	0.1001**** (0.0202)	0.1027**** (0.0199)	0.172* (0.0286)	0.170 (0.0293)	0.151 (0.0356)	0.146* (0.0369)
Observations	819	819	819	819	819	819
	Sub Group: 15-29					
Exposure to robots from 2008 to 2015	0.0975*** (0.0205)	0.1005*** (0.0204)	0.172** (0.0292)	0.171 (0.0299)	0.143 (0.0363)	0.136* (0.0381)
Observations	798	798	798	798	798	798
	Sub Group: 30-54					
Exposure to robots from 2008 to 2015	0.0951*** (0.0194)	0.0970*** (0.0188)	0.156** (0.0269)	0.157** (0.0275)	0.158* (0.0336)	0.159** (0.0353)
Observations	798	798	798	798	798	798
	Sub Group: 55+					
Exposure to robots from 2008 to 2015	0.0939*** (0.0194)	0.0974*** (0.0192)	0.162*** (0.0274)	0.162* (0.0280)	0.156* (0.0342)	0.155** (0.0359)
Observations	798	798	798	798	798	798
	Sub group: High Education					
Exposure to robots from 2008 to 2015	0.0958*** (0.0197)	0.0100*** (0.0195)	0.160*** (0.0278)	0.162* (0.0285)	0.150* (0.0347)	0.154** (0.0365)
Observations	798	798	798	798	798	798
	Sub group: Medium Education					
Exposure to robots from 2008 to 2015	0.0963*** (0.0195)	0.0100*** (0.0193)	0.172** (0.0277)	0.167 (0.0283)	0.164 (0.0346)	0.153 (0.0362)
Observations	798	798	798	798	798	798
	Sub group: Low Education					
Exposure to robots from 2008 to 2015	0.0943*** (0.0201)	0.0957*** (0.0196)	0.159*** (0.0280)	0.160** (0.0287)	0.144** (0.0349)	0.144* (0.0367)
Observations	798	798	798	798	798	798
Controls						
ICT				✓		✓
GMO					✓	✓

Notes: IV estimates of the impact of the exposure to robots on wages. Standard errors are given in parentheses. The coefficients with *** are significant at the 1% level, ** are significant at the 5% level and * significant at the 10% level. Column 4 is the baseline results with no controls. In column 2 also includes a control for the share of ICT. Column 3 controls for changes in output. Column 4 controls for changes in the labour force. Column 5 controls for both the change in output and the level of ICT.

Table 5. *Robust estimates of Wage by gender, age and education in Europe.*

	(1) Pooled OLS	(2) Fixed effects	(3) IV	(4) ICT	(5) GMO	(6) GMO ICT
	Aggregate results					
Exposure to robots from 2008 to 2015	0.1046*** (0.0208)	0.1070*** (0.0189)	0.194* (0.0319)	0.182 (0.0341)	0.147* (0.0414)	0.130* (0.0402)
Observations	882	882	1008	1008	1008	1008
	Sub Group: Men					
Exposure to robots from 2008 to 2015	0.0955** (0.0207)	0.0983*** (0.0186)	0.171 (0.0304)	0.167 (0.0330)	0.151 (0.0398)	0.142 (0.0415)
Observations	819	819	504	504	504	504
	Sub Group: Women					
Exposure to robots from 2008 to 2015	0.1001** (0.0208)	0.1027*** (0.0189)	0.172* (0.0301)	0.170 (0.0328)	0.151 (0.0407)	0.146* (0.0407)
Observations	819	819	504	504	504	504
	Sub Group: 15-29					
Exposure to robots from 2008 to 2015	0.0975** (0.0210)	0.1005*** (0.0189)	0.172* (0.0310)	0.171**** (0.0329)	0.143**** (0.0407)	0.136* (0.0430)
Observations	798	798	798	798	798	798
	Sub Group: 30-54					
Exposure to robots from 2008 to 2015	0.0951** (0.0206)	0.0969** (0.0186)	0.156** (0.0284)	0.157* (0.0316)	0.158 (0.0393)	0.159* (0.0407)
Observations	798	798	798	798	798	798
	Sub Group: 55+					
Exposure to robots from 2008 to 2015	0.0939** (0.0207)	0.0974** (0.0186)	0.162** (0.0295)	0.162* (0.0322)	0.156* (0.0397)	0.155* (0.0410)
Observations	798	798	798	798	798	798
	Sub group: High Education					
Exposure to robots from 2008 to 2015	0.0958*** (0.0208)	0.0996*** (0.0188)	0.160* (0.0301)	0.162** (0.0325)	0.150** (0.0399)	0.154** (0.0418)
Observations	798	798	798	798	798	798
	Sub group: Medium Education					
Exposure to robots from 2008 to 2015	0.0963** (0.0207)	0.0995** (0.0187)	0.172** (0.0301)	0.167 (0.0324)	0.164 (0.0396)	0.153 (0.0413)
Observations	798	798	798	798	798	798
	Sub group: Low Education					
Exposure to robots from 2008 to 2015	0.0943*** (0.0208)	0.0956*** (0.0185)	0.159** (0.0287)	0.160* (0.0318)	0.144** (0.0401)	0.144** (0.0419)
Observations	798	798	912	912	912	912
Controls						
ICT				✓		✓
GMO					✓	✓

Notes: IV estimates of the impact of the exposure to robots on wages. Standard errors are given in parentheses. The coefficients with *** are significant at the 1% level, ** are significant at the 5% level and * significant at the 10% level. Column 4 is the baseline results with no controls. In column 2 also includes a control for the share of ICT. Column 3 controls for changes in output. Column 4 controls for changes in the labour force. Column 5 controls for both the change in output and the level of ICT.

Table 6. *Hausman Test for Employment and Wage Regressions.*

	Employment			
Coefficients	(b)	(B)	(b-B)	sqrt(diag(V_b-V_B))
Exposure to robots from 2008 to 2015	.1011776	.1008384	.0003392	.0015418
Test: Ho: difference in coefficients not systematic	chi2(1) = (b-B)'[(V_b-V_B)^(-1)](b-B) = 0.05 Prob>chi2 = **0.8259** **Threshold:** If this is < 0.05 (i.e. significant at a 5% level) use fixed effects.			

	Wage			
Coefficients	(b)	(B)	(b-B)	sqrt(diag(V_b-V_B))
Exposure to robots from 2008 to 2015	.1243129	.1228183	.0014945	.0020831
Test: Ho: difference in coefficients not systematic	chi2(1) = (b-B)'[(V_b-V_B)^(-1)](b-B) = 0.51 Prob>chi2 = **0.4731** **Threshold:** If this is < 0.05 (i.e. significant at a 5% level) use fixed effects.			

Table 6. *Correlation tables between Exposure in Europe and the US.*

6a - All sectors

	dlEAllEU	dlEAllUS1
dlEAllEU	1.0000	
dlEAllUS1	0.7909	1.0000

6b – Manufacturing sector

	dlEDEU	dlEDUS1
dlEDEU	1.0000	
dlEDUS1	0.7305	1.0000

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