Industry 4.0 Impact on Employment in Portugal
A Special Look into the Metal, Automotive and Other Transport Equipment Sectors & Aerospace Related Professions

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Abstract
Since the first industrial revolution with the invention of the steam engine, there have been three other major shifts in the industrial production paradigm with the second one referring to the mass use of electrical energy and the third to the digitalization and automation of industry. Recently, one of the biggest surges in technological development has been in full force, having been considered the fourth industrial revolution. The term Industry 4.0 was coined as the name that would describe this revolution. Industry 4.0 is characterized by a set of nine technological pillars and its impact is broad as it influences productivity, investment policies, revenue growth and employment. As with all previous revolutions, the increase in technology leads to human labour displacement and, as a consequence, to growing concerns regarding the future of jobs. This work analyses the metal, automotive and other transport equipment sectors, looking into the companies that constitute them, their employees and their robot acquisitions. The objective is to address the concerns regarding the future of jobs, by studying how the increase in number of robots affects the companies’ revenues, the employment numbers in these sectors and the wages earned by the workers. Finally, a special look is taken into professions related to aerospace, aiming to characterize the aerospace sector in the scope of Industry 4.0. Both analyses performed refer to the 2010 to 2016 period.

Keywords: Industry 4.0, Labour Displacement, Future of Jobs, Metal, Automotive, Aerospace

1. Introduction
Ever since the first industrial revolution there have been cases of technological improvements resulting in the displacement of human labour. This effect usually comes accompanied by growing concerns for the day that human labour might become obsolete. Over the course of the last decade, the fourth industrial revolution has gained traction and this has led to a widespread concern regarding the future of jobs, as it is in full effect as of recent years.

Nowadays, there are robots being created all over the globe that fulfill tasks that previously constituted the jobs of thousands of workers. Across several sectors of industry this leads to job displacement and thus might be the source of worsened living conditions for a considerable portion of the world’s population.

Although the studies regarding this rise in technology are limited, the fact that one of the emerging technologies is related to amount of data and its analysis might be seen as a double-edged sword. On the one hand, the fact that more and more data is available creates an increasing difficulty to fully process all of it. But on the other hand, it allows for the possibility of analyses that were previously impossible, as not only the amount of data increases, but the technologies to process it evolve trying to keep up with the rate at which the data quantity does. With the available information, different authors have been working on this industrial revolution’s impact, with names such as Acemoglu and Restrepo [1] leading the way in the United States, or Dauth et al. [2] in Europe.

Considering that studies are limited for nations as developed as the US or Germany, it is no surprise that the processed information in Portugal is even less developed, as it is not an economy of the size of the ones that are usually put under a close scope. Preparing for the future should be a strong concern for all nation leaders, and to do so there must be extensive studies that enable their actions. After realizing that, with an adequate mentality and the proper course of action, the outcome of a high exposure to robots is not of cataclysmic proportions, it becomes apparent that understanding the measures that can be taken to react to said exposure’s increase is of prime importance.
There is a high demand for workforce upgrades and through the analysis of the long-term impact and conduction of strategic planning (role adaptation, recruiting and vocational training) it is possible to not only avoid a negative impact, but to achieve a positive net result (Rüßmann et al. [3]). This article aims to address the impact of the rise in automation level, more specifically robot acquisition, in three different sectors of the Portuguese economy. By taking a look at how the increase in the number of robots affects jobs, the hope is to establish a commonality between how the Portuguese scene is evolving and how the ones described in the literature are.

The other objective is to give some insight into Aerospace related professions, mainly through establishing a parallelism with the sectors of study. With a proper result regarding such parallelism it would be possible to draw conclusions regarding the present effects of automation in the aerospace sector in Portugal.

2. Background

2.1. What is Industry 4.0?

The concept of an industrial revolution was first employed in the 19th century when steam engine powered factories completely changed the paradigm of material goods production. Ever since then, technological developments have been the cause of incredible increases in industrial productivity. Whenever a major technological leap, which leads to a shift in the production paradigm, takes place the term industrial revolution is easy to employ. It is commonly accepted that, besides the first one, there have been two others, as mentioned in [4]: in the early 1900s with the intensive use of electrical energy and the widespread digitalization and automation of industry in the 70s.

As mentioned in [3], in the years since the third industrial revolution there have only been incremental technological advancements. However, this pattern changed and a new change in paradigm is upon us. The rise of new digital industrial technology, on the basis of advanced digitalization within factories and advances in the field of “smart” objects is the major difference that constitutes the shift in paradigm known as Industry 4.0, where the 4 refers to the fourth industrial revolution.

There are nine major advances in technology that contribute to this industrial revolution, as seen in [3]. Many of them are already used in manufacturing, but what is innovative about Industry 4.0 is how these new technologies will transform production by being implemented according to the revolution’s principles. It will be possible to optimize isolated cells, making them work together as a fully integrated, automated and optimized production flow. This will cause drastic increases in efficiency and alter the existing relationships between supplier, producer and costumer. These nine advances are shown in figure 1.

2.2. Impact of Industry 4.0

In general terms, Industry 4.0’s impact is expected to be four-fold [3]: it will manifest itself in terms of productivity, revenue growth, investment and employment.

2.2.1 Impact on Productivity

Labour productivity is required to increase continuously in high-wage countries and it is the core of industrial development and economic growth, according to Schuh et al. [5].

To give a practical example, Rüßmann et al. [3] give Germany as an example. In 2015, the article projected that the embracing of Industry 4.0 by more and more companies would boost productivity throughout every German manufacturing sector by a value between €90 and €150 billion. This is expected to happen due to productivity improvements on conversion costs, which when accounting for material costs represent improvements of 5 to 8%, with the highest levels of improvements expected to take place in the industrial-component manufacturing sector.

2.2.2 Impact on Revenue Growth

Along with the expected changes on the productivity side of the impact, Industry 4.0 will obviously drive revenue growth, as the demand for enhanced, customized equipment is a key factor towards it. Considering the Germany example again, Rüßmann et al. [3] predict that this demand will equate to increases in the order of €30 billion, which amounts to 1% of Germany’s gross domestic product.
2.2.3 Impact on Investment

All across the world there is an increasing willingness to adapt new technologies as to not fall behind when it comes to the expected increases in productivity brought along by Industry 4.0.

In Germany, the expected investment across 10 years, with regards to adapting production processes to incorporate Industry 4.0 is of about €250 billion, according to [3] (which is around 1 to 1.5% of manufacturer’s revenues). In the United States, President Obama launched the Advanced Manufacturing Partnership (AMP) in 2011 with the objective of charting a course for investing and furthering the development of emerging technologies [7]. This group’s report recommended increased investment in US manufacturing facilities and, by 2013, the Obama administration increased the funding for advanced manufacturing by 19% [7]. In China, a plan set towards reducing dependency on foreign technology was allocated €1.2 trillion, which was accompanied by the intent to increase investment in R&D by 1.5 to 2% of their GDP [7]. India had a similar policy with the investment on R&D was equal to 2% of their GDP.

2.2.4 Impact on Employment

Out of the four levels of impact described, employment is the one that causes the highest amount of concern. M. Lorenz et al. [8] pose questions such as whether this wave of industrial evolution will create or destroy jobs, how job profiles will evolve and regarding the types of skills that will be in demand.

Adopting Industry 4.0 will allow manufacturers to create new jobs to meet the higher demand that comes with the growth of existing markets and the introduction of new products and services [8].

However, the creation of new jobs does not automatically equate to a net increase in employment. There will obviously be jobs displaced by computerisation. Frey and Osborne [9] gave the example of machinists, as they estimated their odds of being displaced at an astounding 65%. They allocated that 702 occupations were at risk of being computerised with 47% of all US employment being in a very high risk category. However, not all economies are the same: taking Germany as an example, again, a 6% increase in employment over 10 years was predicted by M. Rüßmann [3] in 2015, with the mechanical-engineering sector as one of the main drivers for this increase, with an expectation of a rise of 10% in jobs. However, like every paper on the subject, the change in required skills is stressed out, as low-skilled workers who perform repetitive tasks are expected to be displaced.

2.3. Impact of Automation on Employment

Although there is some obvious overlap between what is said here and what was said previously, the goal here is to address the impact of automation (autonomous robots) on employment, as it is the main focus moving from here on out.

2.3.1 What is an Industrial Robot?

According to the International Federation of Robotics [10], industrial robots are defined by the ISO 8373:2012 description: "an automatically controlled, reprogrammable, multi-purpose manipulator programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications" - reprogrammable means that the design must allow for motions or auxiliary functions to be changed without physical alteration; multi-purposed means it has to have the ability to be adapted to different applications resorting to physical alteration (physical alteration refers to changes in the mechanical system); axis refers to the direction used to specify the robot’s motion in either a linear or a rotary mode.

2.4. Rise of Robots and Future Prospects

As M. Bahrin et al. [11] refers, the number of multi-purpose industrial robots in Europe alone has almost doubled since 2004. This trend has been continuous and the increase in robots has not been proportional to the increase in workers, as is demonstrated in [2] and [12] (illustrated in figure 2). A similar analysis is shown in figure 3, this time for the Portuguese landscape.

Figure 2: Industrial robots per thousand workers in the United States and Europe (Source: Acemoglu et al., 2018)

There is, without a doubt, a very commonplace concern regarding the spread of robots and its impact on the future of jobs and wages. However, as Acemoglu and Restrepo [12] state, there is not much work done on the equilibrium effects of robots. They estimate the impact of industrial robots between 1990 and 2007 on US local labour markets by establishing a model in which robots compete
Figure 3: Industrial robots per thousand workers in Portugal (Data Sources: IFR & INE)

against human labour in the production of different
tasks to clarify why automation technologies dis-
place workers from tasks they were previously per-
forming. They conclude that, for the US economy,
the number of jobs lost due to robots has been lim-
ited thus far, with only a 0.2% decline in employ-
ment to population ratio. Nevertheless, they are
not entirely optimistic, as their predictions point
towards a 1% drop in the same ratio between 2015
and 2025, accompanied by a 2% lower wage growth.
Acemoglu and Restrepo’s [12] predictions regarding
wages are historically supported by data provided
by Ford in his book [13], here shown in figure 4.

Figure 4: Growth of Real Hourly Compensation for
Production (Source: M. Ford, 2015)

On a slightly different note, Dauth et al. [2], ex-
pose the impact of robots on the German market
and find that they are not job killers, as they have
not depressed total employment. However, their
findings are analogous to Acemoglu and Restrepo’s
when it comes to employee earnings. They make the
case that workers exposed to robot entry in their in-
dustry trade off higher job stability for lower wage
growth, meaning that the effect of robot exposure
on earnings is negative. They still point out the fact
that, since production rises but employee wages do
not, automation causes the widening of the earn-

3. Methodology

The first part of this section will address the initial
datasets which were available. This will be followed
by a summary of the process used to filter those
datasets, as well as the reasoning for that filtering.
Lastly, there will be an explanation of the analyses
performed on the final datasets.

3.1. Initial Sets of Data

All the data used in this work originated from two
different sources. Firstly, there were the databases
with information referring to Industrial Robot ac-
quisition, while the remaining databases regard em-
ployment in Portugal.

3.1.1 Data from the International Federation of
Robotics

The IFR provides data on robot installations by
type, country, industry and application, data which
is collected from nearly all industrial robot suppliers
worldwide and supplemented with data provided by
national robot associations - ensuring the databases
cover the global industrial market [10].

Regarding the available data, the main indicator
is the number of newly installed robots per year,
and the two different variables resorted to are the
robot operational stock and shipment each year.
The operational stock of robots measures the num-
ber of robots currently deployed. While this num-
ber in Japan is determined exactly by JARA (Japan
Robot Association) in a survey, for other countries
IFR Statistical Department estimates the operation
stock assuming an average service life of 12 years
with an immediate withdrawal of service afterwards
[10].

3.1.2 Data from Quadros de Pessoal

Quadros de Pessoal (QP) is a longitudinal-matched,
employer-employee data set [14]. The data is
gathered annually by the Portuguese Ministry of
Labour, including data from all private firms with
a minimum of one wage earner. Each annual survey
pertains to around three million individual workers
and 250 thousand companies. The sample being
analysed covers 7 years, starting off in 2010 and
concluding in 2016, with the number of companies
averaging at 1711 each year and the number of em-
ployees at 59507 for the sectors’ side of the study
and at 30186 for the aerospace one.

The companies’ dataset had the following 5 vari-
ables of interest: year to which the data referred
to, the company’s unique identification number, the

4
class (used to identify the category in which the company is inserted), the two digit code (used to identify the division within the category) and the company’s business volume.

Regarding the employees’ dataset, 11 variables were considered to be of interest: year, unique identification number of the company in which the worker is employed, unique identification number of the employee, biological sex, age, tenure of the employee within his/her company, one digit education level code, four digit profession code, monthly earnings, usual weekly paid hours and remuneration control.

3.2. Dataset Filtering

3.2.1 Data from the International Federation of Robotics

Considering the availability of data, the obvious first step was to narrow down the market to Portugal. Taking into account the data available from Quadros de Pessoal, described in 3.1.2, the following step was selecting the robot data ranging from 2010 to 2016 in order to have information that could be compared with the one regarding companies and their employees. This meant isolating the robots acquired in the metal, automotive and other transport equipment (OTE) sectors, as well as the operational stock at the end of each year.

3.2.2 Data from Quadros de Pessoal

With the automotive, metal and OTE sectors in mind steps were taken to trim down the companies’ database. The first step was to select the companies that were in the automotive, metal or other transport equipment sectors, resorting to the companies’ class letter and class 2 digit code. There was discrepancy between the IFR and the QP codes, as the activity code for manufacturing in the IFR database was a D, while the one used by QP follows the INE (Instituto Nacional de Estatística / National Statistics Institute) [15], using the letter C for manufacturing. With this information, all companies that operated in the alluded to sectors were selected from the initial database for every year ranging from 2010 to 2016.

With the previous restrictions, the total number of companies for the years being analysed came down to the 1500 to 1900 range on each year. The next step was to select the employees that worked in these companies from the other database, which was fairly trivially accomplished by selecting employees who had the same company identification number as the companies remaining in the previous database. The total number of employees for these years came down from the initial three million to the 58 to 66 thousand range.

Finally, for the parts of the analysis where wages and levels of education were looked into, workers that were under some sort of remuneration control and those for whom the education level was unspecified were removed. This reduced the amount of workers available for these evaluations considerably. In order to be sure that the data was reliable across the time period span, a comparison of the amount of workers remaining after the removal each year was done. The reduction was homogeneous, with every year showing a remainder of 83% of the initial number of workers (excluding 2010 which still retained 80% of the initial number). This homogeneity means that the filtering will not cause conclusions to be biased based on the year.

To be able to provide some amount of insight into the aerospace sector, a document made available by INE [16] was thoroughly scanned, with the goal of identifying every profession with some sort of connection to the aerospace sector. This document classifies every profession in Portugal with a 4 digit code, which will be used to identify the selected professions in the QP database. These professions are: mechanical/aeronautical, electronic and telecommunications engineers, other technicians and mechanical inspectors, aircraft pilots, air traffic controllers, electronic aeronautical systems security technicians, aerial and sea transportation services control employees, aircraft engines maintenance and repair technicians and mechanical machinery assemblers (air force personnel did not make it to this list as QP only has private sector companies and employees). The same filtering process described previously was applied here, with the reduction being again homogeneous, presenting a remainder of 88% or 89% of the initial employee number every year.

3.3. Dataset Analysis

After gathering and filtering all the data through the procedures described previously, it is necessary to proceed to analysing the information remaining. This analysis is comprised of three parts, described ahead.

3.3.1 Descriptive Analysis

The first part was a descriptive analysis, which starts with the metal, automotive and OTE sectors, followed by a similar analysis for the aerospace professions. This analysis focused on exposing changes in workforce numbers, education levels, wages as well as the business volume of the companies employing the workforce for the sectors part. These changes are analysed between 2010 and 2016 and are accompanied by the corresponding data regarding the industrial robots stock in order to enable
the latter statistical analysis.

3.3.2 Statistical Analysis

The statistical analysis, once again, started with the analysis of the sectors and followed with the aerospace professions. It focused on the correlation between the several variables obtained in the descriptive analysis and on explaining how they are intertwined through the values of the correlation and determination coefficients. This is followed by exposing the correlation between variables from the sectors and the aerospace professions in order to show that the information regarding robots for the sectors might be used to arrive at conclusions for the aerospace professions.

Along the analysis of the collected data, there is a common usage of the coefficient of determination $R^2$, as described in [17]. Also referred to as the multiple correlation coefficient, its use is more than established in classic regression analysis being defined as the proportion of variance that is explained by the regression model. As such it is useful as a measure of success in predicting the dependent variable from the independent ones.

3.3.3 Linear Regression Model for Wages

Posteriorly to the correlation studies between all variables, a deeper look into the earnings of workers is taken, more specifically workers from the sectors’ side of the study.

The goal of this analysis is to establish the effect of different characteristics of employees on their earnings, in order to better describe this sample of workers. The final objective is to determine the linear regression which enables the prediction of wages based on the different variables accessible in the databases, and thus reinforcing the importance, or lack thereof, that purchasing robots has to these industries’ workers.

The procedure to arrive at the values for this regression is four-fold. The first step is to separate the data to analyse in a training set and a test set. The training set will be utilised to establish the regression model and the test set will serve the purpose of understanding the accuracy of predictions resorting to the defined model.

The following step is to establish a linear model that crosses the dependent variable with all the independent variables in order to analyse which ones have statistical significance. The coefficient used to understand the significance is the p-value and, the smaller it is, the better, as it means that it is more unlikely to observe a relationship between predictor and response due to chance. A p-value of 5% or less is usually a good cut-off point, and the different levels of significance are exhibited through a star rating - one star for values between 5% and 1%, two stars for values between 1% and 0.1% and three stars for 0.1% or less. For lesser significance values there is still the option of a single point, for a value between 10% and 5%, while between 10% and 100% there is no symbol whatsoever.

Thirdly, it is possible to determine the linear regression by looking at the coefficients from the model obtained. The estimate coefficient provides the different $\beta$s, the one from the intercept row gives the constant term, while the other ones give the different slopes, to arrive at an equation of the form seen in equation 1, where i refers to the number of employees and j to the number of independent variables. In this equation y is the dependent variable and x is the value of the independent or control variable j for observation i. To explain the final coefficient, the Standard Error coefficient measures the average amount that the coefficient estimates vary from the actual average value of the response variable.

$$y_i = \beta_0 + \sum_{i=1}^{N} \sum_{j=1}^{n} \beta_j \times x_{ij}, \quad i = 1, \ldots, N; j = 1, \ldots, n \quad (1)$$

Finally, resorting to the prediction tool, it is possible to see how well the obtained coefficients adjust to the data by comparing the predicted results for the test set with the actual values present in said set. The two metrics resorted to in order to evaluate whether the linear regression is a good fit are the Mean Absolute Percentage Error (MAPE) and the Root Mean Square Error (RMSE).

4. Results

As described in the methodology, this section is divided in three parts: the descriptive followed by the statistical analyses and the linear regression study.

4.1. Descriptive Analysis

4.1.1 Metal, Automotive and Other Transport Equipment Sectors

The first set of data to be analysed was the number of robots in these sectors, as it was the variable of interest to which the remaining ones would be mainly compared. In figure 5 it is possible to see how the number of industrial robots increased steadily, with the total number in 2016 being 2899, an increase of 138.2% from the 1217 in 2010.

Regarding the employment numbers, there was an increase of 12.2% between 2010 and 2016, starting at 58305 and ending at 65432 total workers. The increase was a lot more noticeable when considering only employees with a college level of education, with an initial 6023 employees to 9155 in 2016,
which meant a 52% change. It is still of interest that the amount of workers that, at most, completed the 9th grade decreased by 6.4% during the 7 year time span.

Regarding employee earnings, the overall values increased by 3%, from 1169€ in 2010 to 1207€ in 2016. However, for college educated workers there was a decrease of 5.9%, with the average in 2016 being 2076.8€, down from the 2207.2€ in 2010.

Regarding the companies’ side of the market, there is a progressive increase in their business volume, with the variation from 5.60M€ in 2010 to 7.38M€ representing an increase of 31.9%. On the total number of companies, however, there was a decrease of 5.6% between 2010 and 2016, from 1814 to 1712.

4.1.2 Aerospace Professions

The trend regarding employment here is similar to the one for the sectors. In this case the increase is of 7.5%, from the initial 29555 employees to the final 31773. When looking at education levels, the increase in job numbers for those with a college education is of 17.3% while for those with the lower education level described previously there is a 17.6% decrease.

4.2. Statistical Analysis

4.2.1 Metal, Automotive and Other Transport Equipment Sectors

Taking into account all the collected data referring to these sectors, the first step was to establish the correlations between all variables, with a specific interest in how the increase in number of robots correlated to the change in the values of variables from the QP database. There were very high correlations between the number of robots and the total number of employees (0.845), the number of college educated employees (0.994), and the companies’ business volume (0.854). These coefficients indicate a very high likelihood that the number of robots is resulting in an increase in number of jobs (especially for higher educated personnel) and profits for companies.

4.2.2 Aerospace Professions

While the statistical analysis for the Metal, Automotive and OTE sectors focused on the impact that the robot purchase had on different factors, this one focuses on correlations between variables from the aerospace profession and variables from the sectors, to be able to tell how good of a proxy these sectors are to the aerospace professions.

Regarding the number of jobs, the correlations were quite high, enabling the inferring of conclusions regarding the impact of automation on the aerospace sector. For the total number of jobs the correlation coefficient was 0.936, for college educated employees 0.938 and for lower educated ones 0.822. However, the correlations for wages were poor, meaning that the sectors are not a good fit to explain aerospace employees’ earnings.

4.3. Linear Regression for Sector Wages

Firstly, there is a need to address the different variables used for this study. The dependent variable is the logarithm of the monthly wage of an employee in one of the sectors. The two independent variables are the variation of the number of robots in these sectors, measured by the yearly shipment of robots, and the tenure of an employee within his/her company. Finally, several control variables are used: on an individual level, firstly, the education is used, divided in three binary variables as low education, high school education and college education; secondly, there is a binary variable controlling for gender, as it has been established that female employees earn less than their male counterparts [19], [20]; thirdly, the employee’s age is another variable present here, used to control for the worker’s general experience [21], [22]. Lastly, the usual weekly work hours are also used for control, as employees on a limited time schedule will obviously earn less than those working full time. On a labour market level, the sectors are included as control variables, to account for possible differences of pay in each one. Finally, yearly variables are included for every year ranging from 2010 to 2016, in order to control for the business cycle [14].

4.3.1 Descriptive Statistics and Correlations

Table 1 provides descriptive statistics for the sample of employees being analysed, meaning that they allow for the characterization of the sample’s average employee. The variables with a (d) are dummy variables.

The average worker is 40 years old and has worked at the same firm for almost 11 years where
he has a usual weekly work time of 172 hours. He works in a sector which has a yearly addition of 117 industrial robots.

4.3.2 Results

Table 2 provides the results of the regression analysis.

Regarding the control variables, the dummy variables which refer to the years are not statistically significant every year. The 2016 year is not shown, as the regression was built using it as a reference, with the other yearly coefficients being dependent on its value. Age plays a significant role, with the positive coefficient confirming the expectation that, in general, older workers have higher earning levels. The weekly work hours play a predominant and positive role as well, as expected. Regarding the employees’ biological sex, the baseline was set for a female employee’s wage, with the male employee’s coefficient being given as a function of it. Fuchs’s [19] findings still prove true after 48 years, as the coefficient for a male employee is both significant and positive, meaning that being a male employee equates to a rise in pay. The control for the sector also proved relevant, as workers in the metal sector experience a higher coefficient than the other two. Lastly, as was to be expected, education plays a considerable role, with college employees having a much higher coefficient than the rest.

Now looking at the independent variables, it is visible that tenure is relevant at the 0.1% level, meaning it is statistically significant. The tenure coefficient is positive, implying that the longer an individual stays at the same company, the higher his wage would be, which stands to reason.

Finally, looking at the main variable being analysed, the entry of robots in the market shows a negative, statistically significant coefficient. This implies that robot purchases have an overall negative effect on the wages of employees for these sectors. This negative effect shown here is in accordance with the literature, more specifically with the recent findings of Acemoglu and Restrepo [12] and of Dauth [2].

Regarding the errors, as explained in 3.3.3, the results of a prediction vector were compared to the actual values present in the test set. The root mean square error for the sample was RMSE= 0.34096, which equated to a mean absolute percentage error MAPE= 4.1873%.

5. Conclusions

As was thoroughly explained in the literature by both Acemoglu and Restrepo [1], [12], Dauth et al. [2] and Rüßmann et al. [3], the impact of automation in the workforce is not necessarily negative. Although the expected impact regarding wages is negative, when it comes to the amount of jobs an increase is to be expected and even more so for people with higher levels of education.

Regarding the sectors side of this study, the overall number of jobs had a high level of correlation with the number of robots, which was shown to have increased at a considerable rate from 2010 to 2016 in figure 5. Furthermore, the most conclusive result was indeed the correlation between the number of robots and employees with a college level of education. Showing almost a perfect linear correlation, it meets the expectations set in the literature.

Another result that went along with the historical data shown by the OECD [6] was the one regarding business volume. As exposed in figure 7, the productivity levels have increased steadily throughout the years in which the automation level has risen the most. The same can be said here, considering that the business volume of the analysed sectors has such a high, uphill correlation to the number of robots existent in said sectors.

When it came to the earnings of employees, the results obtained in the linear regression study were in line with what was set as the common trend regarding the effects of automation: the increase in robot number in the sectors of study results in a decrease in wages. This conclusion is easy to draw, as the results for all other variables (both control and independent ones) were congruent with previous conjectures.

Finally, this work still showed some results regarding aerospace related professions. As referred previously, the main point that was possible to establish was the correlation between variables from the sectors’ side of the study and their equivalent in the selected professions database.

Regarding the wages, most correlations were poor and, therefore, inconsequential. However, the correlations between the amount of jobs for the professions linked to aerospace and in the sectors were much more satisfying. From these results it is possible to infer that the increase in robots has a similar effect in aerospace profession as it does in the sectors analysed. As predicted in the literature, job growth is expected, mainly for people with high academic differentiation levels.

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Table 1: Summary Statistics

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Table 2: Linear Regression Results

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tional Institute of Statistics for providing the data used in this study.

Lastly, I would like to address my mother: Thank you for everything you’ve done for me throughout my life, being there for everything and anything I ever needed, whether I knew I needed it or not.

References


