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Master in Economic Development and Growth

The automation of abilities, not jobs.

A study of the effects of automation in the
United States from 2000 to 2015

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Abstract: Automation is one of the key topics of the 21st century with many workers concerned about their jobs being replaced by machines. This has led to an ongoing debate to determine to what degree automation is occurring, and which occupations are going to be affected by it. This paper attempts to take a different approach which differs from mainstream authors by focusing on the tasks that each occupation is composed of, rather than the whole occupation itself. To do so I estimate the effect ten abilities, skills or work activities have had on employment and wages between 2000 and 2015 in the United States. An example of my findings is that tasks which include processing information are complemented by automation whereas working in a cramped work space is a bottleneck to automation. Using this new approach, this paper provides useful information on how firms, individuals and policy makers should adapt to an ever-increasing automated reality.

Key words: Automation, United States, abilities, skills, occupations.

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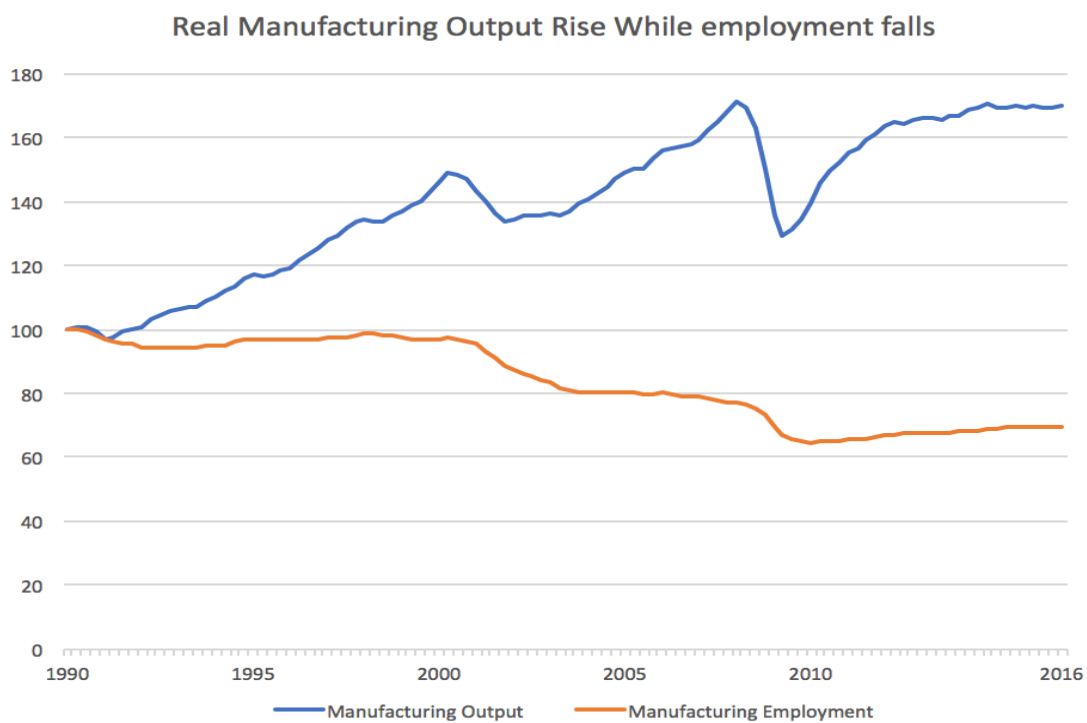
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1 Introduction

One of the big issues of the 21st century is the uncertainty of what will happen to both our jobs and wages in relation to the fact that automation could start replacing even the most cognitive of human occupations. Automation has been crossing new boundaries every year and it has shown no signs of slowing down. Today we can find examples of these new technological capabilities in self-driven cars or news articles that are written by machines. These concerns have risen in a time of scarce job creation and declining wages but with rising productivity levels as we can see in Figure I.¹ This has occurred in the United States for the period 2000-2015 where there is an ongoing debate about lack of job growth and an increasing inequality.

Figure 1: Index of Output and Employment in Manufacturing in the United States (1990-2016)



Source: Graph of own elaboration Data: FRED

¹ Acemoglu and Restrepo (2017) and Brynjolfsson, E., and McAfee, A. (2014)

As we can see in Figure 1, employment in the manufacturing sector has considerably decreased in the period between 1990 and 2016 in the United States whereas manufacturing output has steadily increased throughout the period. This is only an example of economic growth that has been accompanied by a lack of job creation in the last decades.

Automation has been highlighted as a crucial driving force behind these trends in countries like the United States. This is an important issue that needs to be addressed so that firms, workers and policy makers know up to what extent automation is taking place and what abilities and skills are being substituted. This rising interest of researchers on automation has led to various estimations of job destruction. For example, the work by Frey and Osborne (2013) estimates that 47% of US employment is at risk of disappearing due to automation. However, these estimations are based on the prediction of job destruction, not task destruction. This distinction is important given that, while automation can substitute many tasks that nowadays are in the hands of humans, there are others that are still unlikely to be substituted.

The complex nature of each individual job, even as simple as it may seem, is the ultimate protection behind an occupation being completely automated. Take for example an accountant. An accountant will input information into a computer on a daily basis. This task is likely to be very repetitive and monotonous. However, a great share of the value from being an accountant comes from the interaction with other members of the company and contacting clients or providers. Moreover, accountants receive and process information in various formats, may them be digital or physical. This is an example of how one single occupation can contain many activities, some of them automatable and others not. Therefore, it is important to take a deeper look at individual tasks, skills and work activities and analyse what parts of these are automatable.²

Furthermore, automation is now substituting many jobs that were previously seen as complex jobs, that were once deemed to be impossible to be performed by machines. However, the boundaries of what machines can do is constantly being pushed, and if this rate continues, Rifkin (1996) estimated that we could see labour eliminated from factories

² I will be using the terms tasks, abilities and skills interchangeably throughout this paper to refer to the group of the tasks analyzed in this study.

by 2025. These new boundaries are alternating the production functions of many businesses worldwide who are looking towards this new technology to cut labour costs.

Another side of the debate is the new breach in the labour market that is being caused by these new technological advances. Evidence has been found of growth in the number of high income occupations that require high cognitive abilities and human perception. Also, there has been growth in low income manual occupations (Goos et al. 2009). However, middle income occupations are suffering a decline and this is leading to a polarization in the labour market by creating only two groups: low skilled and high skilled jobs. This divergence is one of the main concerns related to global inequality increasing because of automation and the destruction of middle class occupations. On this matter, the World Bank Report 2016 has given further evidence that advanced economies are facing polarization in labour markets and that inequality is increasing. The role of technology on augmenting skills and replacing routine tasks is emphasized as it was in many other periods, including the industrial revolution.

Offshoring is another issue to be addressed. This labour export is a very popular terminology that politicians use to explain current employment tendencies. This given that many jobs have supposedly been offshored to other countries to reduce costs.³ But in fact, a lot of these jobs have been found to be substituted by new upcoming technologies instead.

1.1 My Research Question

Since 2008, various theories have been proposed to explain the high levels of unemployment and stagnant wages that persist in many developed countries despite modest economic growth. This paper attempts to enrich the debate on automation with a new approach by estimating the effects that certain tasks, abilities and skills have had on employment and wages in the 21st century. I will study the United States because it is a good example of one of the most powerful economies in the world that has been having

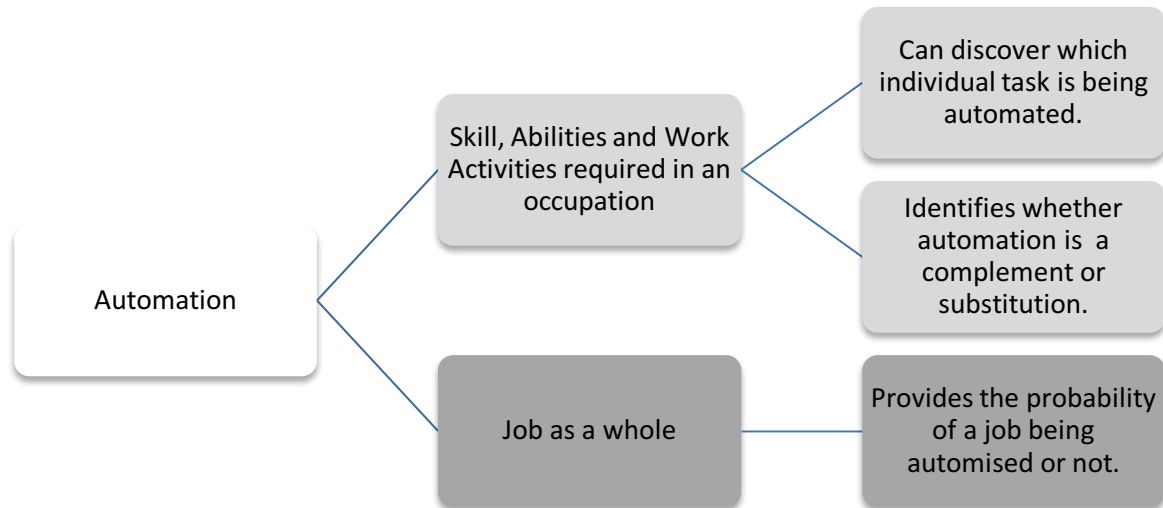
³ Harrison and McMillan (2011)

stagnant wages and a growing inequality. This provides us with an example of an economy where automation is a potential cause for this divergence. Moreover, the United States has a very detailed database on the different tasks that each individual occupation is composed of, thanks to a database called O*NET. This database provides detailed descriptions of all the occupations in the United States. Using this, I dissect the nature of each occupation on the different tasks that compose them. The motive behind this is that no single occupation consists of only one task, but in fact, they are composed of multiple duties that are performed on a daily basis.

By this point, it is important to clarify the distinction between jobs and occupations. Occupation is the vocation of work a person undertakes whereas a job is a post of employment that the person currently fulfils. An example of a job is the definition of an agreement of one person to work for another, whereas an occupation would be the specific trade you are working in, such as a surgeon. This is an important distinction because in this paper I will study occupations and the different parts of it that make it what it is, rather than studying jobs as a general term.

The main motivation behind this work is that current academic research is focused on the concept of “The end of work” instead of “The end of some abilities”. I believe that a more accurate assessment of reality would be to evaluate the individual components of an occupation. This because automation is more likely to complement workers rather than displace them and to substitute certain tasks rather than all of them because of the complex nature of even the simplest of occupations. This is an important factor and one that will take a more important role as technology advances. Several historical examples would be sewing machines making each individual worker more productive instead of simply replacing that person. Another example would be the personal computer, which while it performs many tasks automatically, it also enhances every worker and therefore almost everyone, both from high and low skilled occupations should benefit from it. An example of the potential of looking at each individual characteristic of an occupation is that we can produce occupation profiles and estimate the probability of each part of the profile to be automated.

Figure 2: The thought process behind this work, green representing my study and red represents the current approach.



Source: Graph of own elaboration

This paper aims to explain the relationships shown in Figure II, where I have highlighted in green my approach to estimate where automation is occurring. The main objective is to shed light on the role automation plays on workers. This includes identifying whether they will be complemented, substituted or partially substituted by automation. The present study contrasts the traditional research questions proposed by other authors that solely attempt to produce a numerical estimation on the probability of an occupation to be automated given the special focus on abilities. Therefore, my research question in this work is: *“What effects do different abilities, skills or work activities had on employment and wages during the 21st century in the United States”?*

This work will focus on ten abilities with the objective of finding what effect these skills have had on both the employment and wages. It is important to note that the analysis of all the possible combinations of skills and abilities is beyond the scope of this paper.

To achieve this, I will use an Ordinary Least Squared regression model where I will have employment and wages as the dependent variables and the skills as the independent

variables to quantify the effect of automation. The different tasks that are selected in this study are based on what other authors have estimated in terms of automation from each ability, skill or work activity. My results expect to highlight the tasks that workers have been losing to automation during the first fifteen years of the 21st century in the United States. Moreover, apart from identifying each individual task, I will also perform a secondary test creating two groups: automatable and non-automatable that will be used to provide further evidence as to whether the group of abilities I have chosen are significantly or not affecting wages and employment as a group.

In section II, I will describe the literature that has covered the topic of automation including an analysis of historical trends and estimations by other authors. In section III I will be discuss both the data and the methodology. This will include providing descriptive statistics of the dataset both for my socio-economic variables as well as the data for each ability, skill and work activity. Moreover, I will describe the empirical approach I undertake with the Ordinary Least Squared model and list the models and variables that I will be using. In Section IV, I will interpret the empirical results that I have obtained. I will also refer to the discussion at hand once again to analyse what these finding mean for the current debate. Lastly, in Section V I summarize this paper's main findings. Also, I list the limitations of this work and the possibilities that exist for future studies on this topic.

2 Theory

In this section I will analyse the different literature that surrounds the debate on automation. This includes looking at historical trends and reviewing the debate on automation and how it has transformed over history. Considering the historical context, I will then talk about the different approaches and estimations that have been made by other authors. A comparison of these results will then lead us to analyse the potential theoretical outcomes and evidence of what has happened because of automation and what additional predictions can be made. Then, I will continue the debate on whether it is better to select abilities rather than entire occupations to estimate the potential effects of automation. Here I will highlight the potential of using more individual characteristics of each occupation rather than treating the occupation itself. Finally, I will briefly mention the current political debate on offshoring taking jobs away and whether evidence shows that such theories are true or not. This will provide information to help understand the changes of the labour market that could be misunderstood as offshoring, when it could be a potential case of automation in the economy.

2.1 Introduction to the debate on automation

Automation has been going on in the past in different forms and time periods. Authors like David (2015) indicate that several times over the course of the last two centuries, many occupations have been put at risk of automation, but human labour has not become obsolete. He bases his work on the idea that automation, although designed to replace workers, usually acts as a complement to them, by raising their output which finally leads to a higher demand for labour itself. Another example of this kind of evidence comes from the study by Leontief and Duchin (1984), who analysed the impact of automation on employment for the period between 1963 and 2000. They use a dynamic input-output model to estimate the effects of potential automation in the two following decades. These authors conclude that job destruction may be evaded if more productive workers make businesses expand their production which will lead to the hiring of more workers.

Additionally, other sectors can emerge due to the creation of new sectors, products and markets which leads to more opportunities, or the improved performance of the same market translating into more jobs. On the other hand, if this improved performance does not lead to more jobs, either in the same occupation or in a different one, then we are looking at a situation of automation. These two forces acting against each other are the centre of the debate on automation.

The development of new sectors and the dwindling of others is also a part of the history of automation. Currently there is a new inflow of information technologies that are changing wages in the United States. Wage inequality has been one of the results of this change since technologies could be the force dividing the population in between high wage and low wage workers. According to Aghion et al. (2002) we must analyse the general-purpose nature of the new information technologies and understand how they are influencing wage inequality. This means that we must understand whether technologies are being used by all professions or whether they are only affecting specific occupations. Their estimations on wage inequality show that general technologies transition periods can increase within-group inequality. This suggests that perhaps this new wage inequality is getting worse as each general technology is implemented. An example of a general-purpose technology that became fully available to a large spectrum of jobs and enhanced the productivity of workers across all sectors is electricity. This applies to the current situation where new technologies such as the internet, personal computers and robotics could be leading to a new transition period.

Basu and Fernald (2007) highlight the importance that Information and Communication Technologies have had in augmenting productivity in the United States towards the end of the 20th century. ICT sectors have experienced productivity increases due to the general-purpose technology effect of the productivity advances. They find evidence that increases in productivity in ICT related industries is related with ICT capital growth in the 1990's. These findings prove that ICT related industries are indeed increasing productivity. But the use of this type of technology can imply higher productivity per worker and the automation of many activities that were previously performed by workers. This can lead to these types of industries to be both the new industrial revolution of the 21st century and the reason behind a growing inequality simultaneously.

In the past, technology has evolved and become an influential part in areas that were previously unthinkable. For example, many clinical centres around the world now use computers that can interact with and diagnose patients. This has had unprecedented effects on the number of tasks that have been adopted by machines. Due to the new technologies, abilities such as interaction, language translation, creation of narratives, problem solving and pattern recognition can be now performed by machines (McAfee 2014). On the other hand, certain abilities are considered bottlenecks to automation which present us with protective trends in both employment and wages. This is because if some tasks are difficult (or even impossible) to automate, the security of our jobs and wages could be assured. However, the tasks that are still more vulnerable to automation are those that are more repetitive and ruled by certain algorithms or rules (McAfee 2014). These kinds of occupations are an example of those vulnerable to automation.

Nonetheless, there are certain variables that are hard to control for when estimating automation. For example, the pace at which it will occur due to exterior factors such as labour and political unions. Also, the development of technology and the uncertainty of the different technologies that will become available in the future.

2.2 Estimations by authors

Regarding employment and wages, Acemoglu and Restrepo (2017) find robust evidence of sectors that are vulnerable to automation. Their evidence comes from the analysis of “robots per workers” in commuting areas.⁴ They look at evidence of robots affecting commuting zones to see the impact on the economy. Their conclusion is the adoption of robots in a commuting zone could translate into lower costs for other areas, meaning a possible expansion in employment. But even controlling for this they find further evidence that both wages and employment suffer. However, according to the most recent contributions to the debate, occupations are rarely destroyed by automation. As Bessen (2016) states, since 1950, only one out of two hundred and seventy detailed occupations listings have disappeared. Nonetheless, even though it seems that an occupation does not

⁴ This indicator shows the number of robots per 1,000 workers and has become a useful tool to reveal trends in the automation of jobs.

disappear as such, this does not neglect the truth that job reduction has occurred in certain sectors along with negative wage pressures. But this gives more evidence towards the use of total occupations being more ineffective than analysing some specific abilities.

As stated previously, automation can lead to the elimination of a certain task or ability. This can affect the demand of occupations and affect their wage levels. While technological change may have not meant job destruction by itself, automation could do so. This is because machines reduce the amount of human labour required to produce the same amount of output (Bessen 2016). These results in less workers being required to produce the same amount of output. This technological change is leading to a skill bias that is causing wage inequality to rise in the United States. Evidence so far has been conflicting. It has been affirmed by Violante et al. (2002) that indeed Information technologies are causing changes in the wage structure in the United States and this raises the question of a possible skill-bias that technological progress has. However, much of this new technology is also general purpose technology which has benefited the whole economy. For example, the personal computer, which is used by professions throughout the spectrum.

Depending on the methodology used, technology can be the explanation for wage inequality or not. However, some of these methodologies are not comparable because of certain variables or time periods being composed over different scenarios (Bessen 2016). With regards to the labour market, several changes have been noted including the fact that inequality has been on the rise in the U.S labour market. It is said that those workers that lose their jobs to automation will need to invest in new skills and training to be able to compete for new well paid jobs. Having education developed and providing the knowledge and skills in new technologies to these workers is one of the main challenges that automation presents. This gives way to the possible race between technological advanced and the accessibility to education for workers to keep up. According to David (2015), what has changed the most are the types of occupations available and their respective wages. This highlights the polarization of wages that we have seen in recent years. This represents the trend that while high and low class jobs are growing, the middle-class sector is not.

Furthermore, it is also important to consider whether the estimations are signalling that automation could be complementing or substituting workers. David (2015) considers that

workers who perform tasks that are complemented by automation will be benefited from this new technological revolution. It is almost important to note that, in between 1980 and 2010, David (2015) finds further evidence that occupations at the high end of the skill ladder grew faster in terms of wages than in previous decades.

Hunter and Lafkas (2003) compare empirically the effect on wages that the implementation of different kinds of Information Technology have had in bank branches. These authors find that IT work practices that improve the quality of organizational information are positively correlated with wages. However, they also identify that the problem is also a structural one, with public investments focused on digital companies which is leading to natural monopolies in these kinds of sectors. This lack of competition is leading to more educated people with better networking capabilities to receive most benefits from this structure in society (World Bank Report 2016). This divide is known as one of the main reasons behind the divergence in wages and employment that has been discussed earlier.

2.3 Individual tasks versus occupations

The perils of automation have been observed throughout many periods of economic history. It has taken many different forms ranging from the sewing machines during the industrial revolution replacing the occupations of many workers to “*driverless*” cars attempting to replace human drivers today on our streets (Waldrop 2015). Many different studies attempt to quantify the effect of automation. For some, automation can lead to an occupation being performed by a machine which means we can calculate the automation probability of that occupation in question. However, other works such as the one from Arnt et al. (2016) argue that people are not completely replaceable, but instead certain tasks within their occupations are. Thus, they focus on certain abilities, skills and knowledge that are automatable. This can be useful in evaluating how certain tasks, abilities and knowledge can reduce both wages and employment. This paper is in line with this view. I argue that the automation of abilities presents a more accurate assessment since even the simplest of occupations comprehend a large variation of activities, some of which may be substituted by machines and others that are more resistant to change.

Previous studies have provided different estimations for the effect of automation on both wages and employment. In 2013, Frey and Osborne (2013) published “The Future of Employment”, which produced estimates of probabilities of occupations to be completely automated. Their paper has been at the centre of the debate for the last couple of years due to their estimation of 47% of occupations in the United States at risk of being automated. While this paper has catalysed this recent debate, it has also generated remarkable criticisms. For example, Arnt et al. (2016) claim that it is not a job, but rather certain tasks that can become automated. In their paper, the main argument is that not entire occupations are displaced by machines, but rather only certain tasks. They perform a cross-country comparison, and provide a much more conservative estimation of 9% occupations at risk of becoming automated. This remarkable difference comes mainly from the fact that even the workers doing the most automatable occupations perform tasks that are not automatable. Hence, the work of Frey and Osborne (2013) is considered to have overestimated the probability of automation.

Additionally, the Mickinsey Global Institute’s report (2017) predicts that many repetitive physical activities could be automated. This report estimates that automation could raise productivity growth by 0.8-1.4% annually. These estimates also present a more conservative scenario than Frey and Osborne’s. They argue that less than five percent of occupations can be automated, and around sixty percent of occupations have at least 30 percent of their activity that could be automated. According to them, many middle-skill occupations involving physical activities in predictable environments, as well those related to the collection and processing of data have a higher chance to become automated. This is an important analysis that provides insights to what certain abilities and skills could be considered automatable which is essential for research such as this one.

However, estimations are inevitably affected by macroeconomic variables and these studies do not consider the new occupations that will appear by the time that year comes. It is possible that shifts in occupations will come from agriculture to manufacturing and service sectors. This is expected to lead to the creation of many new occupations with the new available technology.

Alternatively, Bessen (2016) performs an analysis using the dependency of computer use as the variable of interest. He presents a calculation on the probability of computer-

intensive occupations of becoming automated, and tests its effect on relative employment growth by occupations or industries. This author finds that occupations that require the use of computers have presented less job losses due to automation. This implies that there are other forces acting in response to automation such as changing demand and labour substitution. However, Bessen's approach is based on many assumptions. Firstly, it is not guaranteed that those occupations using a computer will have more automation. In fact, we could say the opposite given that computers could be considered a general-purpose technology. Perhaps, as it is in fact stated by other authors, automation is going to lead to more complementary effects than substitutions. This means that computer dependent occupations may be complemented rather than substituted by automation. Moreover, as we are going to see in this paper, there is evidence to believe that it is more of a complement.

The decision to provide a further analysis on abilities rather than occupations is motivated by the supporting literature indicating that automation has more of a partial rather than complete effect on occupations (Arntz et al. 2016). To identify these abilities is a complex task as Frey and Osborne demonstrate in their work. They assembled a large team of experts to identify the capabilities of current technology to automate work tasks. Based on their argument we can identify three human characteristics that currently appear difficult to automate: creative intelligence, which involves the development of original ideas; social intelligence which relies on social interaction; and perception and manipulation, which require manual dexterity and interaction with unstructured physical environments. These are the main "bottlenecks" to automation and are part of the abilities that later I will put to the test in my own econometrical work. There is also additional work that identifies bottlenecks to automation such as the Mckinsey Report (2017).

On the other hand, several activities are likely to be automated. Physical activities top the list especially in predictable environments (Mckinsey Report 2017) which coincides with the findings of Frey and Osborne (2013). Moreover, activities such as data processing and collection are also susceptible to automation. This represents up to 51% of the U.S economy and this is one of the catalysts for the recent debate on automation.

2.4 Offshoring

Offshoring can be sometimes confused by automation and the links between these two phenomena are not clear. To start, ignoring offshoring can lead to severely overestimate automation. However, the bias can go the other way and offshoring can be overestimated due to changes in automation trends.

To discuss these recent trends in employment and wages, it is also important to understand the role offshoring plays. The decline in both the employment and wages can many times be caused by of the effect that offshoring has on the economy. This can make us overestimate the effects of automation when in fact the cause is offshoring. This means that while occupations might not be disappearing through automation, offshoring can reduce costs by sending labour costs to cheaper production countries who have a comparative advantage. However, it could be the case that these jobs are not going anywhere, in fact, they could be exactly where they were before, just that they are now performed by a machine. Furthermore, the work of Ebenstein et al. (2014) attempts to quantify this by using individual worker data from population surveys from 1984 to 2002. This work shows evidence supporting the theory that globalization and offshoring negatively affect wages in developed countries such as the United States. Globalization applies downward pressure on worker wages through reallocation of workers. This happens because people are forced away from manufacturing occupations into other ones. They find evidence of wage falling between twelve to seventeen percent.

Offshoring has also had negative consequences for wages inside the United States. These concerns could be deepened even more with the tradability of services becoming greater in recent times. However, this effect is still very modest to be significantly influential. But this is occurring especially in IT occupations. The work of Derimogly (2008) estimates that in the case of services we will see a maximum of ten to twenty of occupations offshored. This is important because it means that structural changes in both employment and wages in the service sector occur in large proportion because of factors such as automation rather than offshoring.

The causes behind job destruction can be sometimes attributed to offshoring. However, it is shown that automation can also be responsible for this. In the work of Harrison and

McMillan (2011) they have found evidence of over four million jobs destroyed during the period 1977 to 1999 because of offshoring in the United States. This has occurred because of U.S businesses searching for lower costs and specializing in their new comparative advantages. However, they find that offshoring only accounts for one quarter of job losses in the U.S with factors such as technological change and trade being also very important. This means that in the United States, there is an important quantity of jobs that are disappearing that cannot solely be explained by offshoring, meaning that automation is singled out as the one of the main possible reasons behind this trend. These concerns are enlarged when we consider that many parts of the productive process that is offshored is also being automated. This shows us that automation may not only be affecting developed economies but also developing ones where these imported jobs are so critical for their development.

2.5 The new approach

This paper is primarily focused on the most recent wave of automation that is being debated on in recent years. This wave is characterized with automation that is occurring in sectors that were before out of reach. The big question that arises is whether occupations are no longer being created faster than they are being destroyed. After 1990, many new technologies arrived including the internet and robotics, that replaced already existing labour technologies. This is leading to many labour-intensive tasks being automated. Acemoglu and Restrepo (2017) find evidence that this technology is indeed influencing our current labour markets and that it is one of the big threats to occupations in the 21st century.

We can see that the debate on automation has been going on for a long period of time. Work of other authors attempts to address the debate by providing estimates of the probability of a job being automated. However, the fact is that some automation can be expected to substitute jobs completely while others will be considered to just complement them. Hence, it would be of more use to decompose each individual occupation into certain abilities, skills and work activities and identify which parts of the occupation are being automated and which ones are not. This will not only solely help us answer the

question of whether automation is taking jobs away and reducing wages or not, but it will also help us understand the current situation relating the divergence in salaries, the increasing productivity and the declining offshoring. Moreover, this approach attempts to group the variables into two groups: automated and non-automated to find evidence that the selected abilities for each group are significant on. The purpose of this is to find further evidence of significance of each group on both wages and employment.

With this information, I can make more accurate predictions about which areas of an occupation are going to be partially automated or whether it is going to be fully automated. This could help enlighten the current young population who are acquiring skills, knowledge and abilities to be able to identify which sector will be available to be performed by humans in the future. Using a diverse selection of abilities and skills including both bottleneck abilities and expected automatable ones, we can obtain certain trends that would be very useful not only for informative reasons but to base future studies on. However, despite the quantification of this effect has already been attempted, there is a niche to find evidence about which skills abilities and tasks are being negatively affected, which ones are being complemented and which ones are bottlenecks to automation.

3 Data and Methodology

This paper selects ten abilities, skills and tasks, and estimates their effect on wages and employment due to automation between 2000 and 2015. The analysis would shed light on which of these tasks are more vulnerable to automation and which ones are more protected against it. My hypothesis is that automation will complement some of these tasks but will substitute others. To identify the variables I am going to test, I partly rely on the work of Frey and Osborne (2013) where they identified abilities that are bottlenecks for automation. The next section will explain which databases have been used in the past to perform this test and reason the one I will be using in this work.

3.1 The Data

To start, it is important to clarify the tasks that I have selected to undertake this research. I decide to focus on analysing five abilities that have been found in the literature to be difficult to automate and five abilities that have characteristics that make them easier to automate, as found by previous researchers. Identifying the abilities that belong to each of these categories is a difficult task since it can be very subjective. For the non-automatable abilities, I rely on the previous work of Frey and Osborne (2013) where they identify ten skills that are bottleneck to automation. In their study, they use data from O*NET and attempt to estimate the probability of automation of each occupation. From their work, I identify four skills: Finger Dexterity, Cramped Work Space, Persuasion and Assisting and Caring for Others as abilities, skills and tasks that are difficult to automate. Moreover, I use critical thinking, which I base on the definitions of the Mckinsey (2017) reports to be a logical choice for a skill difficult to be automated.

On the other hand, to identify the automatable abilities I use the definition of automatable tasks from the literature such as the Mckinsey Report (2017). This allowed me to select the following skills: Recording Information, Processing Information, Interacting with Computers, Monitoring Processes and Precision. These abilities usually represent repetitive tasks and are ones that current technological capacity can substitute.

Table 1: My selection of non-automatable and automatable abilities

Non Automatable	Automatable
<p style="text-align: center;"> Finger Dexterity Cramped Work Space Persuasion Assisting and Caring for Others Critical Thinking </p>	<p style="text-align: center;"> Processing Information Interacting with computers Documenting/Recording Information Monitor Processes, Materials or Surroundings Control Precision </p>

The meaning of each individual ability, skill and work activity can be found in the following table according to the definitions that appear on O*NET:

Table 2: Variable Names and description

Variable Name	O*NET Name	Definition
FingDEX	Finger Dexterity	The ability to make precisely coordinated movements of the fingers of one or both hands to grasp, manipulate, or assemble very small objects.
CrampedWork	Cramped Work Space	How often does this job require working in cramped work spaces that requires getting into awkward positions?
Persuasion	Persuasion	Persuading others to change their minds or behavior.
Caring	Assisting and Caring for others	Providing personal assistance, medical attention, emotional support, or other personal care to others such as coworkers, customers, or patients.
CriticalThinking	Critical Thinking	Using logic and reasoning to identify the strengths and weaknesses of alternative solutions, conclusions or approaches to problems.
ProcessInfo	Processing Information	Compiling, coding, categorizing, calculating, tabulating, auditing, or verifying information or data.
Usecomputer	Interacting with computers	Using computers and computer systems (including hardware and software) to program, write software, set up functions, enter data, or process information.
Recordinfo	Documenting/Recording Information	Entering, transcribing, recording, storing, or maintaining information in written or electronic/magnetic form.
Monitor	Monitor Processes, Materials or Surroundings	Monitoring and reviewing information from materials, events, or the environment, to detect or assess problems.
Precision	Control Precision	The ability to quickly and repeatedly adjust the controls of a machine or a vehicle to exact positions.

Source: Table of own elaboration. Definitions from O*NET.

The reason I focus on ten abilities are twofold. To start, I want to perform a thorough analysis that allows me to describe and study the effects that each ability has had on employment and wages. This would not be possible if I examine a high number of tasks. Moreover, introducing hundreds of combinations in this model would decrease the degrees of freedom and severely affect the significance of the results.

To be able to quantify these abilities I use the O*NET database. This database is the most comprehensive source of information on what each individual occupation in the United States consists of. It includes information for a total of seven hundred and two occupations that I intended to use in this work. By attempting to use all occupations my goal was to not bias my dataset by leaving out a certain sector or industry. However, due to lack of data for some of the professions and given that some occupations did not have an identical IC-code between the US labour bureau and O*NET, the dataset finally included five hundred and eighty jobs for employment and five hundred and twenty nine jobs for wages.

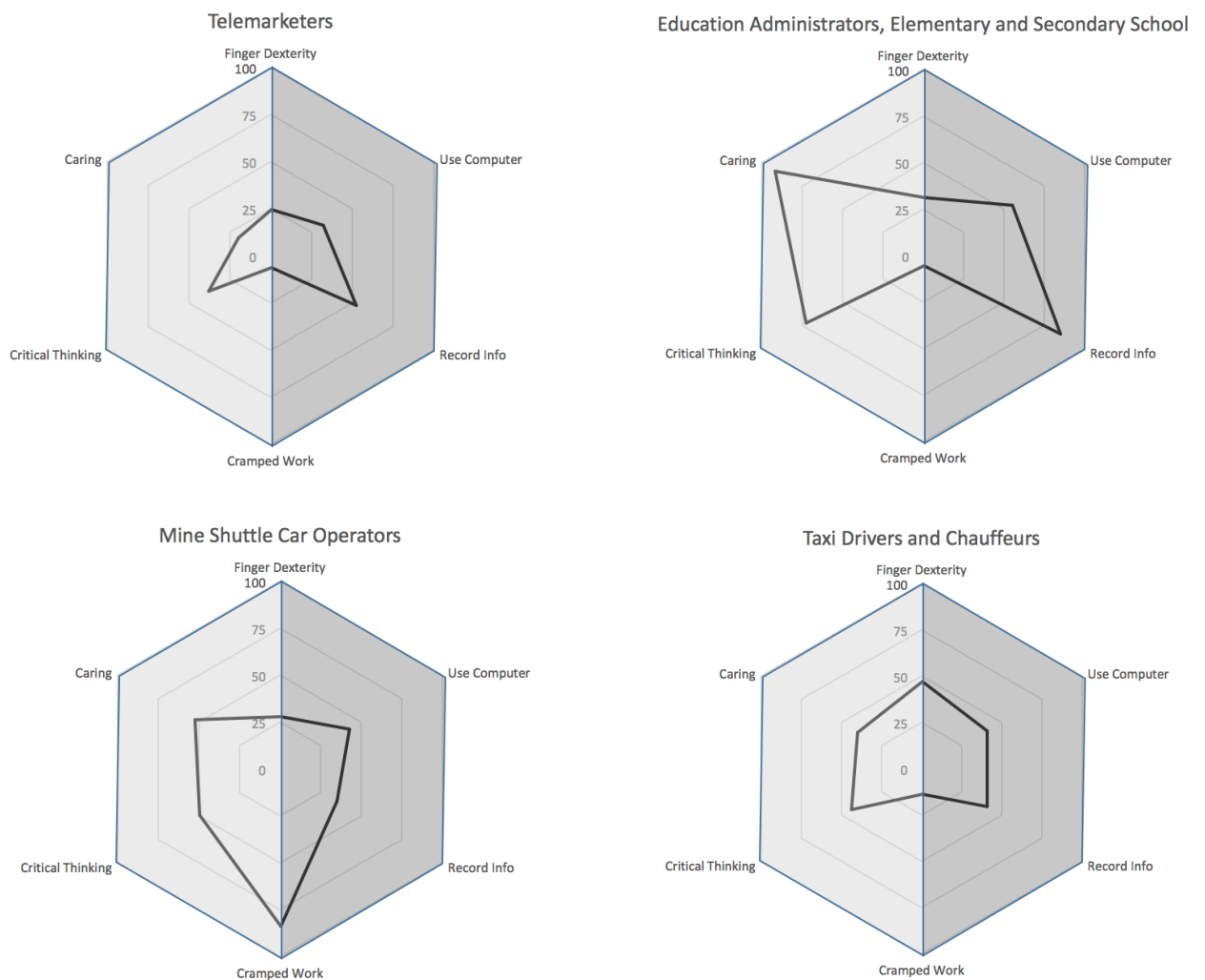
The O*NET database contains individual data for each ability in two formats. Firstly, it states the level of each ability required in each occupation. Secondly, it designates the level of importance that each ability has on the performance of each occupation. The degree of importance is explained on the O*NET website as a rating that *“indicates the degree of importance of a particular descriptor is to the occupation”*. The possible ratings range from Not important (1) to Extremely Important (5). This is then converted into a 0-100 format and published in the website. This level of importance of each ability was calculated from surveys performed by O*NET for the United States.

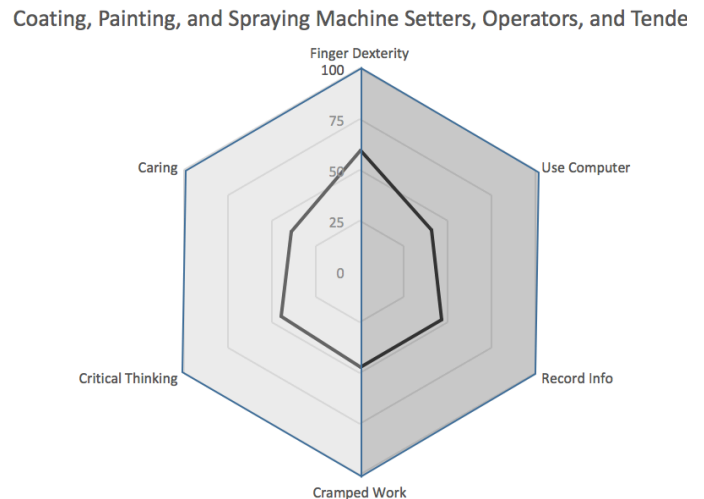
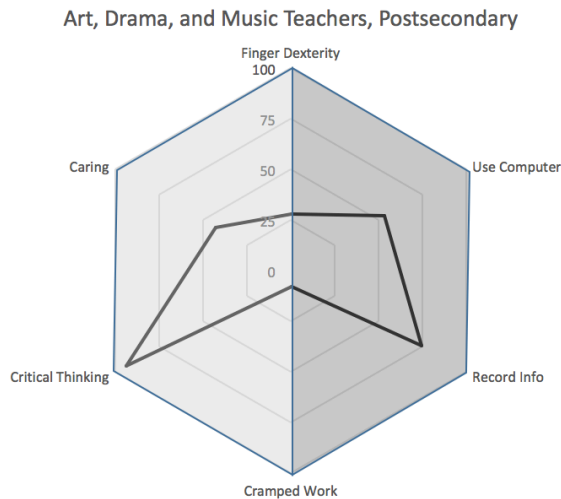
In this work, I use the importance as the indicator since it represents both the percentage of time spent using this ability and the importance of a task on the worker’s occupation. With this indicator, I can generate profiles for each individual occupation. These profiles show the ability requirements for all occupations. The radial graphs shown in Figure 3 present the profiles for six selected occupations. I selected these specific occupations as an example of the different types of distribution of abilities and skills we can find over different jobs. The abilities highlighted in green are considered non-automatable abilities (Caring, Critical Thinking and Cramped work), whereas those in red are expected to negatively affect your employment and wages (Finger Dexterity, Use Computer, Record Information).

Nonetheless, it is important to keep in mind that not all abilities are included in these graphs given that including all ten abilities would make it graphically difficult to visualize and to understand. However, by selecting of couple of key bottleneck and automatable abilities we can see which profiles were more prone to be automated in between 2000-2015.

As we can see professions such as Telemarketers and Mine Shuttle Car Operators have more automatable profiles than those of Education administrators or Art and Drama teachers who have a more varied profile. Most of the abilities and skills that are performed by Telemarketers appear to be automatable whereas those of Education Administrators are more balanced between automatable and non-automatable. In these graphs, we can see the difficulty that arises when it comes to completely automating an occupation due to the different tasks that need to be performed. Even occupations believed to be easy to automate, such as the ones found under Coating, Painting, Spraying Machine Setters, Operators and Tenders due to their repetitive motions, are found to encompass a very varied skill base including Caring for Others.

Figure 3: Radial graphs of the profile of six different occupations.





Source: Graphs of own elaboration, Data: O*NET database

The descriptive statistics of the abilities that I am going to analyse in this study can be found in Table 3, where we can see the average importance that each ability has for the five hundred and eighty occupations used in this research. As we can see each individual ability is well distributed among all the five hundred and eighty professions that I am analysing in this study. In Table 3 we can see that there is a broad distribution for all the occupations ranging in between 0-100. Among the automatable abilities, we can see that the highest average is critical thinking and the lowest is cramped work space. Whereas, among the non-automatable abilities we can see that processing information has the highest average of 60.64 level and monitor precision is the lowest with 38.77 level.

This implies that all the jobs in the labour market have a broad amount of different abilities, skills and work activities. For obvious reasons, certain abilities such as Cramped Work Space are less present in the labour market as they belong to more specific professions rather than, for example Finger Dexterity, which is applies in almost any activity up to a certain degree. We can also notice that the jobs have a high variance with almost all the abilities having representation of occupations close to 0 and almost 100 in others. This also assures that we do not have an overrepresentation or underrepresentation of any group of occupations. This is relevant since in my database we have had to reduce our total observation amount to 580.

Table 3: Descriptive statistics of each ability

Descriptive Statistics						
	Variable	Obs	Mean	Std. Dev	Min	Max
Automatable	FindDEX	580	46.12	13.97	0	81
	CrampedWork	580	28.31	21.72	0	94
	Persuasion	580	41.61	12.74	16	81
	Caring	580	46.28	19.50	7	99
	CriticalThinking	580	60.67	11.13	31	94
Non-Automatable	Processinfo	580	60.64	15.13	12	100
	usecomputer	580	57.18	26.08	1	100
	recordinfo	580	60.14	18.83	7	99
	monitor	580	39.76	19.67	0	94
	precision	580	38.77	22.77	0	94

Source: Graph of own elaboration

In this Table, we can see the tasks that are going to be considered as non-automatable and automatable in the model. In addition to analysing the effect of each individual task on employment and wages, these groups will be used to generate average ability importance levels to create two additional variables: Automatable and non-Automatable abilities. We will then attempt to find the significance of these variables to find out whether these tasks are indeed complements or substitutes to labour.

Given that the employment and wage levels of occupations are influenced by an important number of aspects in addition to abilities, it is necessary to control for the socioeconomic environment. This will allow me to really capture the effect of automation as intended in this research. To start, I control for the percentage of women participating in each individual occupation since the rate of change in employment and wages may be influenced by the presence of a more female workforce. It is important to control for this because it is a possibility that women's wages have converged or diverged towards equal

pay in recent years despite the recent slowdown in convergence (Hegewisch and Hartmann 2014). I also control for the percentage of the workers according to their ethnic background distinguishing between White, Black, Asian and Hispanic. The reason for this is that there may be variation in wage growth between different ethnic groups could have been different throughout this period. All this data was obtained from the U.S Bureau of Labour statistics which provides a detailed database from 1990 to 2015 for each individual occupation. However, for this study I will be using the data corresponding to the year 2015.

Additionally, I obtained the educational level that would be required for each individual occupation. The education levels were obtained from the US Bureau of Labour statistics and these were recovered in text format that described each individual level of education. This text description ranged from a doctoral degree to no formal educational credential. To transform this into a numerical format I estimated the years of completion required for each stage of education and subtracted the obligatory education. This provided me with an index of post obligatory education studies that are required for each occupation. The last control variable used in this research is the unemployment rate of each occupation. This is relevant since those jobs with higher available people searching for a position in that occupation could pressure wages to be lower.

Table 4: Descriptive statistics of my socio-economic variables

Descriptive Statistics					
Variable	Obs	Mean	Std. Dev	Min	Max
Women	580	37.76	29.33	0.5	97.5
White	580	65.81	14.02	7.6	93.9
Black	580	10.85	6.34	1.2	39.9
Asian	580	5.74	5.27	0.5	37.3
Hispanic	580	16.79	10.57	0.3	62.7
Yearseduc	580	3.38	3.03	0	11
unemp	580	4.96	2.14	1.7	10

Source: Graph of own elaboration. Data: From U.S bureau of labour statistics.

In Table 4, we can see the descriptive statistics of the socio-economic control variables used in this study. As we can see the average percent of women in the selected occupations for the year 2015 is 37.7%. Moreover, the table displays the different percentages of each ethnic group on all occupations where we can see the different proportions of each group, with the labour force predominantly being white. We can see the average years of post-obligatory education is 3.38 years, and the average unemployment rate is 4.96 percent. We can see that for education, the highest educational requirement for an occupation is eleven years while there exist others that require 0 years. Also, we can see that there is a wide range in the unemployment levels among the occupations, with some occupations having as low as 1.7% unemployment rates and others with as much as 10%. This indicates that in my dataset I also have a broad selection of jobs including those where a lot of people are unable to find a job in that occupation and others where there is almost no more workforce available for it.

Lastly, I have the dependent variables employment and wages for the United States for the period 2000-2015. These are obtained from the U.S Bureau of labor statistics for all the occupations available. To use them in my cross section I, calculate the change in these variables for the period. I also convert the dependent variables into logarithms to reduce the variability of the distribution of my data. My dependent variable wages is used in wage per hour format and employment in percent of active population employed in that occupation.

3.2 The Model

The methodology used in this research follows an Ordinary Least Squared (OLS) model. This method will permit me to regress the abilities against both wages and employment, while controlling for the socioeconomic environment of each occupation. The baseline model used in this research is as follows:

$$Y = C + \alpha_1 + \alpha_2 \dots + \alpha_x + \beta_1 + \beta_2 \dots + \beta_x + \varepsilon$$

This study uses a linear regression to attempt to tackle the issue of how much a certain ability (the β 's in the previous equation) can affect employment or wage (Y) considering socio economic control variables (α). The dependent variables are calculated as the

difference in the logarithm of employment and wage levels at the beginning and ending of the period. The specific OLS regression for each dependent variable are as follows:

Model (1)

$$\begin{aligned} \% \Delta \log Wage(t) = & C + \alpha_1 Women + \alpha_2 Black + \alpha_3 Asian + \alpha_4 Hispanic + \\ & \alpha_5 Yearseduc + \alpha_6 Unemp + \beta_1 FingDex + \beta_2 CrampedWork + \beta_3 Persuasion + \\ & \beta_4 Caring + \beta_5 CriticalThinking + \beta_6 ProcessInfo + \beta_7 UseComputer + \\ & \beta_8 Recordinfo + \beta_9 Monitor + \beta_{10} Precision + \varepsilon \end{aligned}$$

Model (2)

$$\begin{aligned} \% \Delta \log Employ(t) = & C + \alpha_1 Women + \alpha_2 Black + \alpha_3 Asian + \alpha_4 Hispanic + \\ & \alpha_5 Yearseduc + \alpha_6 Unemp + \beta_1 FingDex + \beta_2 CrampedWork + \beta_3 Persuasion + \\ & \beta_4 Caring + \beta_5 CriticalThinking + \beta_6 ProcessInfo + \beta_7 UseComputer + \\ & \beta_8 Recordinfo + \beta_9 Monitor + \beta_{10} Precision + \varepsilon \end{aligned}$$

Here we can identify the independent variables I mentioned earlier. This includes controlling for the percentage of Women participating in each individual occupation (Women). Also, the percent of different Ethnicity existing in each occupation distinguishing between Asian, Hispanic, Black and White (Asian, Hispanic and Black while omitting white as the base variable). Moreover, I control for the years of post-obligatory Education (Yearseduc). Finally, the unemployment rate for each individual occupation to control for those jobs that have excess of supply (Unemp). This analysis will show how each ability has affected wages and unemployment for the period in question.

Additionally, I will group the abilities and skills between automatable and non-automatable abilities to attempt to find the overall importance of such tasks. To create these variables, I will calculate the average importance level of the abilities of each group and then regress it against Wages and Employment. This will provide supplementary information about the global significance of these variables and the direction they have on both wages and employment. This specification will look like the following:

Model (3)

$\% \Delta \log Wage(t)$

$$\begin{aligned} &= C + \alpha_1 Women + \alpha_2 Black + \alpha_3 Asian + \alpha_4 Hispanic \\ &+ \alpha_5 Yearseduc + \alpha_6 unemp + \beta_1 automatable \\ &+ \beta_2 nonautomatable + \varepsilon \end{aligned}$$

Model (4)

$\% \Delta \log Employment(t)$

$$\begin{aligned} &= C + \alpha_1 Women + \alpha_2 Black + \alpha_3 Asian + \alpha_4 Hispanic \\ &+ \alpha_5 Yearseduc + \alpha_6 unemp + \beta_1 automatable \\ &+ \beta_2 nonautomatable + \varepsilon \end{aligned}$$

The objective of these last two models is to find global evidence inside both groups of automatable and non-automatable tasks. This will provide further validation on whether automation is indeed occurring at a global level in the vulnerable abilities I listed in table 1 or not. To construct these variables, I took the average of each individual ability, skill and work activity for both the automatable and non-automatable tasks and generated these two new variables. This models purpose is to support my selection of groups and find evidence that the average of the group is significant. This is also a new approach and presents the opportunity to group up certain abilities and provides the flexibility of being able to test for different groups of them.

The effects expected of each different type of ability on wages and employment is not straightforward. The abilities that have been substituted due to automation are expected to negatively affect both wages and employment. However, if automation is complementing workers and increasing their productivity, then we could expect the wage to increase to represent this increase in productivity. Moreover, we could expect the

employment levels to go down since less workers are required to produce the same output. However, this effect is not certain since increasing productivity could also translate into an expansion in the amount of jobs available. Finally, if an occupation has many tasks, abilities and work activities that are not automatable then we could expect positive trends for both employment and wages.

Lastly, it is important to mention some of the limitations of this model. The main one is that these regressions will not include a panel dataset but a cross section analysis. The reason for this format is that, while employment and wages are available for every year in the period, the abilities, skills and work activities are only available for 2015. Moreover, some of the socio-economic data was unavailable for some occupations. Hence, I have had to omit one hundred occupations for employment and one hundred for wages but none of those omitted were of a specific sectors or industries, hence I do not anticipate that this will significantly bias the results.

As we have seen, the model I propose is oriented at estimating the effect of these ten individual abilities on wages and employment controlling for socio-economic variables with data from the U.S Bureau labour of statistics. This will permit me to obtain a regression that I can contrast with results from other works such as that of Frey and Osborne (2013) and in the Mckinsey Report (2017).

4 Empirical Analysis

Table 5: Main Results Table OLS Regression

		Dependent Variables			
		(1)	(2)	(3)	(4)
VARIABLES		Wage	Employment	Wage	Employment
Independent Variables	FingDEX	-0.0002 (0.5628)	-0.0026** (0.0118)		
	CrampedWork	0.0003* (0.0966)	0.0018*** (0.0043)		
	Persuasion	-0.0001 (0.6451)	0.0006 (0.6129)		
	Caring	0.0002 (0.1606)	0.0013** (0.0252)		
	CriticalThinking	0.0005 (0.2387)	0.0039** (0.0246)		
	Processinfo	-0.0003 (0.3125)	-0.0023** (0.0261)		
	Usecomputer	0.0005*** (0.0023)	-0.0005 (0.4895)		
	Recordinfo	-0.0002 (0.3254)	0.0021** (0.0250)		
	Monitor	0.0002 (0.3507)	-0.0014 (0.1172)		
	Precision	-0.0002 (0.4790)	0.0002 (0.8805)		
	Automation			0.0004 (0.1688)	-0.0000 (0.9681)
	AntiAutomation			0.0009** (0.0252)	0.0057*** (0.0001)
	Constant	-0.0294 (0.2879)	-0.1970* (0.0643)	-0.2954*** (0.0036)	-0.0560** (0.0298)
	Control Variables	YES	YES	YES	YES
	Observations	529	580	529	580
	R-squared	0.1937	0.2075	0.1824	0.1448

Robust P-Values in parentheses
 *** p<0.01, ** p<0.05, * p<0.1

Table 5 shows the results from the Ordinary Least Squared regression. The model was done looking for confidence levels of 99%, 95% and 90%. As we can see in these results, we find evidence of some variables to significantly influence either wages or

employment. Starting with the results for the automatable tasks, we can see that Finger Dexterity negatively affects both wages and employment rates but is only significantly for the latter. The definition of Finger Dexterity according to O*NET is: *“The ability to make precisely coordinated movements of the fingers or both hands to grasp, manipulate or assemble very small objects”*. This finding is a surprising result and is contrary to what the team of Frey and Osborne (2013) had estimated for this ability. When analysing this kind of technology, we can see that modern assembly lines of components such as phones or computers are mainly performed by machines. Hence, if the nature of the assembly is repetitive and continuously monotonous these results show that workers are not required for this task. Additionally, it seems that this kind of technology does not make certain individuals more productive or create more jobs of these occupations in the period.

After Finger Dexterity, we can find that three of our variables of interest in the possible non-automated group are positive and significant. These abilities are Cramped Work Space, Assisting and Caring for Others and Critical Thinking. All three of these variables are significantly impacting employment in a positive way, with critical thinking affecting significantly positive the wage also. This is exactly what we could expect from these kind of variables since these are supposedly the activities in an occupation that are considered out of technological capacity to be automated. Cramped work space, or an environment that is not consistently the same when working in it, can be difficult for machines to adapt to. It is usually only in areas where the working space does not change that machines can be usefully implemented. Moreover, caring for others and critical thinking are both occupations that are considered to be very human sense oriented while caring for others implies knowing the person and emotions that machines often lack as well as reacting to others. Critical thinking can be considered complex for a machine to perform since it evolves situations the decision-making process must take in many variables that only the full range of human perception can input. Surprisingly, Persuasion has no significant effect on either Wage or employment. This result implies that during the period 2000-2015 there is no evidence that those occupations involving a high degree of persuasion were either difficult or easy to be substituted by machines.

Regarding automatable abilities, we can see that the results are a lot more varied for both wages and employment. Interestingly for the wage regression, occupations where the use of a computer is intensive are significantly and positively affecting wages. However, although not significant we can see that the sign flips for employment. This suggests that,

while those workers who are complemented with a computer in their occupation are having higher wages, they are not creating more jobs than those that were destroyed by automation. On the contrary, it seems that their wages are decreasing. This is an interesting effect and provides evidence that computer use is in fact a complement towards workers. It also must be mentioned that nowadays in many jobs having a computer is mandatory, so this skill is not new, but rather a norm for even the most unskilled of occupations. This means that it is making the workers in these occupations more productive, hence the pay rise, but at the same time not generating more jobs for other people to perform this task. The argument is that a computer is a general technology that is applied to all sectors, both low and high skilled inclusive. Recording information is the exact opposite of this case. As we can see in table 5, people whose job where recording information is important, are seeing their wages decrease or stay stagnant (non-significant variable) but the employment in that occupation during this period in the U.S is going up for these kinds of professions. This is significant at a five percent level.

This is surprising since this task is supposedly automated by computers since they are very time and resource efficient dealing with data. However, the reason for this variable to not show significance and provide the opposite direction than expected can be because of its definition in O*NET: *“Entering, Transcribing, recording, storing or maintaining information in written or electronic/magnetic form”*. The fact that such data can be input writtenly means that it does not solely imply sensor recording. This means that occupations such as a secretary would record some of the information on paper instead of on the computer. However, in Processing Information we can see evidence in the regression of a decrease in employment, which is also significant, and a negative trend in wage which is not significant. This implies that while those professions inputting data may not be automatable, processing it has seen a large decline in the percentage of workers. A real-life example of this is lawyers, and how they no longer must look through large paperwork of previous cases and they can just quickly use a computer to find the case they require. This kind of occupations that involve this activity have seen a significantly negative trend at the beginning of the century and looking forward we can only expect it to continue. Finally, both operation monitoring and Control Precision are not significantly affecting wages or employment. This can be because of the broad nature of both jobs, where operation monitoring also includes the monitoring of workers not just

machines (a more human activity) and control precision which includes many inputs and adjustments that are still performed by workers.

From these results, we can interpret the percent change in my dependent variables due to the logarithms. For example, if the importance of cramped worked space increases by 10 points on the O*Net scale of 0-100. Then this means a 0.3% percent increase in wages and a 1.8% percent change in employment. Another example is processing information. Where if the same increase of importance is applied then there will be a 0.3% decrease in wages and an 2.3% employment. The interpretation of these numbers is very useful for interested parties to quantify the exact effect of these abilities, skills and work activities on both employment and wages. Below in Table 6, we can see a summary of the different directions that each ability, skill and work activity had in this study:

Table 6: Results and significance by direction

Wages in the United States 2000-2015 period

<u>Positively Affected by</u>	<u>Negatively Affected by</u>
Cramped Work Spaces*	Finger Dexterity
Using a Computer***	Persuasion
Monitoring	Processing Information
Caring for others	Recording Information
Critical Thinking	Control Precision

Employment in the United States 2000-2015 period

<u>Positively Affected by</u>	<u>Negatively Affected by</u>
Cramped Work Spaces***	Finger Dexterity**
Persuasion	Processing Information**
Caring for Others**	Using a Computer
Critical Thinking**	Monitoring
Recording Information**	
Control Precision	

Source: Of own elaboration, representing significance level at 90, 95 and 99 percent level

In the Table above we can see clearly how each different skill, ability or work activity has influenced wage and employment for each occupation. We can see several coincidences for both employment and wages, with some exceptions such as Persuasion and Using a Computer.

In the second part of this empirical exercise, we can see the variables Automation and Anti-Automation which represent the original group of variables depending on whether I consider them to be automatable or not. When this regression is performed on both variables for both wages and employment we see that automation is not significant but positive for wage and negative for employment. This shows that overall the five tasks in occupations that I have selected to be automatable have clearly not had a significant effect on the market in between 2000 and 2015. We would expect this variable to be significantly negative in both cases if the tasks were detrimental to the labour market and substituting rather than complementing workers. However, as we can see individually, the automated variables are not significant. Hence, it is to no surprise that our joint variable is not significant either. On the other hand, the anti-automation variable is positive and significant in both cases. This tells us that in this case we have found evidence for these skills and abilities to be having positive effects on employment and wage trends for the 2000-2015 period. This finding proves that these skills, abilities and work activities can be considered bottlenecks to automation and provide evidence that while some parts of occupations are in decline, others are in growth. Moreover, these kinds of occupations are having not only increased numbers of employed people but also increasing wages through this period.

4.1 Discussion

From my results, we can see that it is possible to identify certain trends from each ability and skill for the 2000-2015 period. Overall, the abilities I selected for automatable and not automatable are varied. We see that some of those abilities that had previously considered by other papers to be automatable or non-automatable have been correctly deduced. However, other abilities as for example Finger Dexterity, which was previously considered to be a bottleneck to automation (Frey and Osborne 2013) in my studies show that it has negative effects on both employment and wages in the period 2000-2015. One

of the key interesting variables is using a computer that while it does not have a significant effect on employment, it has seen a rise in the wages people perceive from having a job that contains it. This finding almost provides proof towards Bessen (2016) work that having a computer does in fact increase your chances of being automated. However, the increasing wages of computer use occupations means that computers are in fact complements not substitutes to workers.

A positive indication for future jobs is that we have seen that several abilities appear to positively affect both wages and employment. Their growth through the 21st century means that they are the growing abilities and skills that have provided and may continue to provide employment to workers. This includes tasks such as: Manual dexterity, working in a Cramped Work Space, Fine Arts, and Critical Thinking. Most of these abilities are confirmed in my work to have had a positive effect on both employment and wages. Although looking at historical trends may not provide us with estimations or predictions for future trends. There are certain abilities and skills that can be in a period of decline or growth. However, despite the clear limitations of this study and the conclusions that can arise from it, I have shown how useful it can be to identify each individual ability and skill. As it generates a lot more complex and precise results of what is going on.

As for my results for the idea of generating two new variables that represent automatable and non-automatable abilities we can see the potential to be able to generate these variables and obtain an overall significance. This helps us provide a clearer image on the direction of groups of variables. In this case, they were used to split the ten variables I have. However, this technique could possibly be used to group up certain types of abilities to be able to find out which different groups are affected. It is also important to highlight that while I did not obtain significant results for automatable abilities, by changing the selection of variables we are analysing, we can obtain very different results. In O*NET there is a large size of variables available hence permitting studies like this one to have countless combinations of possible regression models.

5 Conclusion

The objective of this work was to identify how different work profiles could affect employment and wage trends due to automation. Performing an OLS regression on the O*NET dataset has allowed me to point out certain abilities to be significantly linked to the decrease of both employment and wages. On the other hand, I have reaffirmed that indeed there exists certain abilities and tasks that encourage people to continue using them actively in the workplace for the foreseeable future. Although, this work is unable to give a complete picture of how every single ability and skill affects the labour market, the purpose of demonstrating the capability of this data to be used in this manner was the main goal that this work has achieved. By physically drawing profiles and searching for significance in each individual ability, skill and work activity it is possible to better understand automation and whether it is a substitute or a complement to the current workforce. The econometrical model for employment had more significant variables than the wage model. However, this all comes down to the selection of abilities that were chosen for this study. In my case a total of five abilities were selected for both automatable and non-automatable using references from other authors. This work has provided a different approach to that of Frey and Osborne (2013) who estimated the automation of each individual profession rather than identifying the automation of each individual ability which would be a more accurate assessment to be able to get a more detailed picture of automation. Having precise estimates for each individual ability, skill and work activity has furthered the understanding we now have on how different routines in a workplace have changed over the 2000-2015 period.

In this work, we have been able to see the potential of analysing the importance of each individual skill in the workplace. We have seen varied results among each task with some interesting conclusions. Some of the main findings can be summarised in variables such as that of computer use. Related to this we have found evidence that computers increase wages while decreasing employment opportunities in those occupations. This furthers the

evidence that computers are in fact a complement to the work force and not a substitute. We have found evidence for other variables such as Cramped Work Space to be a bottleneck for automation and this confirms the findings of other authors. Another example of this in this work has been caring for others where we have seen further evidence for an activity which is difficultly automated. These kinds of activities have been on the growth for the period 2000-2015 and this presents a positive outlook towards their future values. However, this is of course not certain since this work only analysed historical trends, without providing a future estimate. On the other hand, we can find examples of specific tasks that are on a declining trend and that could end up disappearing to automation. These occupations contain abilities such as processing information and finger dexterity. These represent tasks that have been on decline over the period and that represent cases of automation substitution. Moreover, in this work I have also taken automation and non-automated abilities as groups and generated two new variables. With these I have proven that the group of five abilities have I have selected as bottlenecks for this study have proven to be also jointly significant when averaged. This is further evidence that reflects that these five abilities indeed have the status of bottlenecks and reflect the expected result. However, my automated group variable was not significant. This result is somewhat surprising and represents that the skills, abilities and work activities selected for this work do not represent an accurate selection of automatable abilities for this period. However, it was beyond the scope of this paper to attempt to broaden too much the scope of all the possible combinations of abilities, skills and work activities.

The practical implications are various. First, it allows us to evaluate current trends in education and job training to see what sectors people should be training for. Those sectors that are becoming somewhat extinct must be looked at and revaluated to not overlap with automation. Moreover, workers need to continuously educate, train or develop their skills to be able to be useful. This could mean for them to specialise in tasks that are less automatable. This paper also emphasizes the importance of how policy must be focused more on complementing technology rather than solely trying to generate jobs. The proposed future of less jobs available in the labour market is yet very far away. A lot of activities and skills remain in human territory and the jobs of tomorrow are still unknown so hence making a prediction is very hard. Although looking at the trends of 2000-2015,

has helped us clarify the general direction that the economy is taking in terms of what abilities, skills and work activities are on the rise and on the decline in the United States.

The limitations of this study begin with the lack of data to be able to construct a panel dataset. This would provide us with a more accurate representation of what has occurred to each ability over the 2000-2015 period. This would require the O*NET database to survey every single year to be able to provide information on how different occupations have changed during a period. An example of this limitation is that now technology such as computers and the internet are most likely more used now in professions that they were in the year 2000. Hence, we should have to control for these changes. Moreover, without this we are limited to using an average decline over a period that has been homogenous, including significant external shocks such as the financial crisis of 2008. Another limitation that exists is the unbiased selection of abilities that must be chosen to be able to perform this regression. This is because the number of abilities, skills and work tasks that exist is very high and including all of them in an econometrical model like this would perhaps dilute the possible significance of each individual ability.

Moreover, regarding the individual selection of abilities this study had to be based on the predictions of previous paper. However, the nature of this paper is not dependent on that these selections were accurate. In fact, we find some contrasting results at an empirical level with some of those estimations. It did however present itself as a limitation in the second part of my empirical exercise where I had to group up occupation characteristics into two groups because they were based on other authors perception's. It would be interesting to repeat this study with other tasks to see the different results that could be obtained with different combinations of selected abilities. A further limitation of this study is the fact that depending on the variables you select, as mentioned previously, there is great variability in the results. This does not imply the model being not robust, just that the nature of the model with so many different abilities, skills and work activities and O*NET being available from O*NET, implies some subjectivity.

In the future, it would also be interesting to expand this research to all abilities and skills and jobs available. This would provide more accurate estimates for Socio Economic Variables and applying it other countries around the world. Moreover, it would also be of interest to be able to predict such changes in developing economies. Additionally, the construction of a panel dataset with considering data that is currently unavailable for each

year such as how important each ability is for a job changes over time. It would also be of interest to redefine automatable skills and recreate this variable since it would be interesting to find concrete evidence on automation having detrimental effects on both wages and employment. This work does not find supportive evidence of automation occurring in all occupations through the abilities, skills and work activities selected for this study. Hence, it would be interesting to pursue this question to find evidence for this. It would also be interesting to be to apply this extend this study into the inequality debate. By grouping up abilities, skills and work tasks among low skilled and high skilled jobs to identify which jobs are being automated according to their skill level and estimate inequality changes. This in turn could lead to an interesting debate on the universal basic income as one of the potential solutions to this inequality, by providing a guaranteed income to those workers that have been technologically displaced.

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