Automation and Unemployment

Does the academic debate support the belief that 4.0-technologies will lead to mass unemployment?

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1. Introduction

During my research on the Fourth Industrial Revolution, I stumbled upon conflicting numbers regarding the impact of modern technologies on employment. The question of how susceptible jobs are to computerization and the future of employment appears to be a point of major contention within this line of research. After having taken a more detailed look at the research on the subject, I came to the conclusion that much of the public debate in Germany surrounding technological development and unemployment has been characterized by a high level of anxiety, often exaggerated by the circulation of intimidating numbers without proper context. Historically, concerns over automation and the possibility of induced unemployment are not new. Early examples include the “Luddite” riots that took place in England between 1811 and 1816, when new machines were introduced in the wool-finishing trade, causing workers to riot in an attempt to prevent the employment of these new technologies. More recently, an article published by the public intellectual David Precht claims that approximately half of all currently existing jobs will be wiped out by 2030 (Precht/Broy 2017). The underlying data for this claim, among many others, is derived from a study by Carl Benedikt Frey and Michael A. Osborne, who place 47 percent of total US employment in a “high risk” category – i.e., jobs that can be expected to be automated relatively soon. The findings of Frey/Osborne stand in stark contrast to other studies that come to different conclusions about the susceptibility of jobs to automation. There is also much disagreement about the various factors that determine and influence how automation will progress in the future. While the past decades have witnessed an enormous rise in computing power, coupled with a growing availability of big data and significant technical advances in areas such as Machine Learning (ML), these developments have not led to employment declines (see for example: Arntz et al. 2019: 20-21). However, labor markets in most advanced economies have been undergoing major changes, with increasing shares of both high- and low-paid jobs at the expense of traditional middle-class, routine-intensive occupations.

Simultaneously, the boundaries of what can be automated are continuing to shift, with automation methods no longer being limited to problems requiring algorithms with well-defined steps. As a result, it remains unclear how labor markets will develop in the near future.

1.1 Hypothesis and methodology

This paper seeks to a) contrast the widespread fears about technology-induced unemployment with the scientific debate, and b) to analyze how the nature of technological change within production processes is often misunderstood as the simple replacement of labor with capital. The first chapter will put forth a short history of automation and computerization in order to contextualize the changes workers are facing today. The second chapter explores the study conducted by Frey/Osborne, its findings and its methodology. In addition, another study will be analyzed in order to contrast the different methods and conclusions. This chapter aims to, at least partially, explain the differences between the different numbers and to highlight the problems in applying the methodology of Frey/Osborne to the case of the German labor market. The last chapter will attempt to capture the different factors and considerations involved in predicting how new technologies will affect automation at the workplace. The goal of this chapter is to show that automation does not simply imply a replacement of labor by capital, but rather that there are much more nuanced processes at work that contribute to a change in the structure of the labor market rather than mass-unemployment. The hypothesis of this paper is as follows:

> "*The current scientific debate does not provide evidence for the widespread belief that technological development will lead to mass unemployment. Automation, currently and despite recent advancements, still has its limits.*"

The inquiry into the future of labor in an increasingly computerized world is important because automation affects workers, their lives, and their families. Furthermore, policymakers need to understand the processes at work in order to sufficiently prepare for the significant changes that will inevitably affect the composition of labor markets.

2. A short history of automation

Throughout history, technological change and its capacity for economic disruption and displacement has caused humans to worry about their own impending uselessness. From the Industrial Revolution onward, the debate among prominent economists in Britain centered on how technological progress would affect workers and whether technological innovation, including its capacity for economic disruption, would be worthwhile in the long run.[1] In his *Principles of Political Economy and Taxation*, David Ricardo concluded that while the application of new technologies and the resulting productivity increases should be viewed as a general good, the "substitution of machinery for human labour [might] render the population redundant and deteriorate the condition of the labourer [sic!]" (Ricardo 1817: 282). However, as did most of his contemporaries, Ricardo distinguished temporary dislocations of labor from possible long-run employment effects. Similarly, Karl Marx, albeit from a different perspective, argued that although technological unemployment contributed to the immiseration of workers in the short run, it would eventually lead to widespread prosperity (Mokyr 2015: 34). Others, such as the British writer Thomas Mortimer, decried the machines that "would exclude the labour of thousands of useful workmen [sic!]" (Mortimer 1772: 72).

The major innovations that drove the Industrial Revolution can be divided into four main groups: power technology, metallurgy, textiles, and a "miscellaneous category of other industries and services" (Mokyr 1990: 210). These technologies greatly contributed to the increased mechanization and "deskilling" of production. Whereas many aspects of manufacturing previously required skilled artisans, work could now be broken down into smaller, specialized, components that required less skill but more workers to perform (Braveheart 1974: xvi). Furthermore, developments in continuous-flow production enabled

[1] The Industrial Revolution is usually dated between 1760 and 1830 (Mokyr 1990: 207).

workers to remain stationary while completing different tasks using specialized tools. Mass produced individual and interchangeable components could now be assembled into complex products through a set sequence of operations. Yet while the first assembly-line was documented in a biscuit factory in Deptford, Britain in 1804, it was not until the late nineteenth century that continuous-flow processes were adopted on a large scale by corporations such as the Ford Motor Company in the US (Mokyr 1990: 337). As steam and waterpower technologies as a power source improved over the course of the nineteenth century, production facilities grew larger in size and productivity gains were steadily realized through the combination of labor and capital. The general pattern characterizing the late nineteenth century can be summed up as follows: physical capital complemented unskilled labor instead of replacing it (Fry/Osborne 2013: 9). These developments were accompanied by both resistance and a shift in attitudes towards technological innovation, particularly in Britain.[2] Overall, the literature suggests that although economic displacement did occur, large segments of the working population, particularly unskilled workers, benefitted from mechanization, as is evidenced by the gradual improvements in real wages of British workers during this period (Feinstein 1998: 649).[3] Finally. the evidence does not demonstrate that technological unemployment actually occurred on a large scale in Britain (Mokyr et al. 2015: 34).

A shift took place with the transition into the twentieth century. The diffusion of electricity as a source of power and the replacement of traditional manufacturing production by mechanized assembly lines reduced the demand for unskilled manual workers with certain occupational tasks. Electrification allowed many stages of the production process to be automated. Whereas traditional assembly lines, characterized by a strong division of labor, required large numbers of relatively unskilled human operatives with specialized tools,

[2] Mokyr et al. compare the better-known British protests, like the Luddite (1811-16) and Captain Swing (1830-32) riots to the "Occupy Wall Street" movement and argue that the role of these upheavals has been greatly exaggerated (Mokyr et al. 2015: 34).

[3] Skilled male craftsmen in particular were displaced by the introduction of machinery, by changes in the organization of production, and by the rise in female employment in traditional male occupations (Feinstein 1998: 651).

the introduction of more complex machinery increased the demand for skilled blue-collar workers (Fry/Osborne 2013: 10). In addition, the introduction of typewriters, calculators and mimeo machines reduced the costs of information processing tasks and contributed to a growing share of white-collar nonproduction workers, rapidly increasing the importance of clerical occupations. As Acemoglu argues, these technical changes favored more skilled workers, contributing to a sharp increase in wage inequality (Acemoglu 2002: 7). Morgan and Katz find that between 1850 and 1910, in the US, there was more growth in high skill jobs and relatively less decline in low skill jobs, compared to middle skill jobs – a process they call "hollowing out". In other words, there is a discontinuity in the impact of capital on the demand for skilled labor between the nineteenth and twentieth century (Katz/Morgan 2013: 2). However, even though certain occupations and occupational tasks were eliminated during this period, the overall demand for labor did not decrease.

New fears about mass unemployment in the US were stoked by the so-called Computer Revolution that began with the introduction of commercial computers in the 1960s.[4] The cost per computation steadily declined between 1945 and 1980 and the first industrial robots were introduced in the 1960s. Airplane reservations could be completed using self-service technology by the 1970s, telephone operators became obsolete, and by 1980 bar-code scanners and cash machines were being employed on a large scale throughout the retail and banking industries (Gordon 2012: 11). The first personal computers were made available in the early 1980s and their capacity to process words and create spreadsheets eliminated repetitive typing and enabled repetitive calculations to be automated. Concerns over automation and joblessness during the 1950s and early 1960s were so prevalent that in 1964, President Lyndon B. Johnson established the *Blue-Ribbon National Commission on Technology, Automation, and Economic Progress*. The commission was tasked with confronting the "productivity problem of that period – specifically, the problem that productivity

[4] A *TIME* magazine story of February 24, 1961 voiced its concern over the so called "Automation Jobless", stating that while in the past industries had hired more people than those that had been put out of business, this was not the case with new industries. In consequence, the jobs of unskilled or semiskilled workers were bound to be eliminated by automation (Autor 2015: 3).

was rising so fast it might outstrip demand for labor" (Autor 2015: 3). The commission ultimately concluded that employment would not be threatened by automation. However, it viewed the reality of technological disruption as severe and recommended several policies, including a guaranteed minimum income for families, using the government as the employer of last resort, the expansion of free education in community and vocational colleges, and individual financial sponsorships for economic development (Autor 2015: 4).

In the following decades, the steady price decline in computing costs created strong economic incentives for businesses to substitute labor for computer capital. The substantial declines in clerical and administrative occupations in the US, between 1979 and 2009, can be viewed as a consequence of routine tasks being increasingly codified in computer software and performed by machines (Acemoglu/Autor 2011: 133). Many middle-skilled cognitive and manual tasks, such as book-keeping, clerical work, repetitive production, and monitoring jobs, can be characterized as routine tasks. Yet there are certain limits on which tasks can be automated using computers. These limits depend upon the ability of a programmer to specify a problem, to quantify the criteria for success and to write a set of procedures or instructions for the machine to execute (Acemoglu/Autor 2011: 20). Acemoglu and Autor refer to these tasks as procedural, routine activities. Overall, the declines in routine-intensive employment have resulted in an increased polarization of national labor markets across the globe, with high-skill employment and low-income service occupations expanding, accompanied by a hollowing-out of middle-income routine jobs (Arntz et al. 2019: 1). This is evidenced by the analysis of occupational polarization in the EU by Goos, Manning and Salomons (2010). While these developments are problematic in their own right, the concerns about mass unemployment due to the automation of "codifiable" tasks proved to be unwarranted. One of the reasons for this is that the supply of skills kept pace with the demand of skills over most of the twentieth century, as successive cohorts gained increased access to public secondary and higher education (Goldin/Katz 2007: 16).

More recently however, the technological barriers that traditionally put limits on the tasks that can be automated have been reduced. Computing power continues to rise at incredible rates, as does the amount, quality, and availability of data. At the same time, there have been significant breakthroughs in machine learning methods. Complex tasks that previously only humans could do now appear increasingly automatable. Recent examples include voice and image recognition as well as self-driving vehicles. Against this background, a new wave of angst has resurfaced, with researchers arguing that machines may be able to match or surpass humans in certain types of tasks in the near future.

3. A comparison of two studies

3.1 Fry, Osborne, and the occupation-based approach

In short, technological progress can have two competing effects on labor. First, technology can substitute for labor. The consequence of this process is a *destruction effect* which forces workers to reallocate their supply of labor. Second, there is the *capitalization effect* which describes the allocation of capital into industries with relatively high rates of productivity, resulting in an expansion of employment in those industries (Fry/Osborne 2013: 3). Historically, the capitalization has played a predominant role. This is because workers have managed to adopt and acquire new skills by means of education (Goldin/Katz 2007: 16). Yet in light of the rapid advances in machine learning, driven largely by an approach called deep learning, the concern about the potential impact of automation on employment is growing. Machine learning, as defined by Brynjolfsson et al. (2018), is a

> sub-field of artificial intelligence (AI) that studies the question "How can we build computer programs that automatically improve their performance at some task through experience?"

In addition, Brynjolfsson et al. categorize machine learning as a "general purpose technology" – a technology that is pervasive, improves over time, and generates complementary innovation. More importantly, machine learning has the potential to performs certain types of tasks better than humans, particularly those involving image and speech recognition, natural language processing, and predictive analytics (Brynjolfsson et al. 2018: 43). With computerization entering more cognitive domains of work, the destruction effect of automation may become more prevalent. As stated previously, this chapter seeks to analyze the Fry and Osborne study. Its purpose is to outline which aspects of their methodology lead to their conclusion of 47 percent of total US employment being at risk – i.e., automatable.

Fry and Osborne build on the task model of Autor et al. (2003), which lays out a two-by-two matrix that distinguishes between different types of occupational tasks, with *routine* and *non-routine* tasks on the one axis, and *manual* versus *cognitive* tasks on the other (Fry/Osborne 2013: 4).[5] However, computerization during the twentieth century was mostly confined to manual and cognitive routine tasks, whereas recent technological advances have allowed computerization to spread to domains commonly defined as non-routine (ibid.: 16). The authors argue that the task model may not be able to predict the impact of computerization on employment in the twenty-first century. In order to quantify how recent technological progress might impact employment in the near future, Fry and Osborne draw upon recent developments in the engineering sciences, including particular advances in machine learning, data mining, machine vision, computational statistics and other sub-fields of artificial intelligence. In addition, they examine the application of machine learning technologies in mobile robotics, with the goal of determining the extent of computerization in non-routine manual and cognitive tasks. As Fry and Osborne explain,

> recent technological breakthroughs are, in large part, due to efforts to turn non-routine tasks into well-defined problems (Fry/Osborne 2013: 14).

[5] Tasks are defined as routine if they follow explicit rules that can be specified in computer code and accomplished by machines. The distinction between manual and cognitive tasks depends on whether a task relates to physical labor or knowledge work. The task model by Autor suggests that a complete substitution of labor will be confined to routine tasks (Autor 2013: 26).

Having large amount of data is important because it allows the performance of an algorithm to be evaluated and improved.[6] For an algorithm to substitute for human labor, it must be able to manage the many contingencies that humans are naturally able to identify and act upon. With big data being widely available, machine learning algorithms are already being applied to a wide range of non-routine cognitive tasks, such as healthcare diagnostics (e.g.: chronic care and cancer treatment diagnostics), financial analysis (e.g.: automated decision-making, stock market analysis, personalized financial advice), and software development (e.g.: bug detection).

Fry and Osborne conclude this part of their analysis by identifying a clear trend: computers are challenging humans in a wide range of non-routine cognitive tasks (ibid.: 19). The same holds true for the computerization of non-routine manual tasks, with improved sensors and big data offering solutions to a variety of engineering problems. As the costs of robotics decline and technological capabilities continue to expand, robots are becoming increasingly autonomous and can be expected to gradually replace workers in a wide range of non-routine manual occupations.

After elaborating on the application of recent technological innovations on non-routine tasks, Fry and Osborne then proceed to derive additional dimensions required to understand the factors involved in determining which jobs are susceptible to computerization. This is achieved by identifying the technical problems that engineers need to solve in order for specific occupations to be automated. These so-called engineering bottlenecks are divided into 1) perception and manipulation tasks, 2) creative intelligence tasks, and 3) social intelligence tasks. Although Fry and Osborne argue that some of these engineering bottlenecks can be alleviated through the simplification of tasks, they concede that

[6] An example given by Fry and Osborne is handwriting recognition. In order to determine whether an algorithm correctly recognizes certain styles of handwriting, a large amount of data containing a variety of styles is required.

> many non-routine occupations that involve complex perception and manipulation tasks, creative intelligence tasks, and social intelligence tasks are unlikely to be substituted by computer capital over the next decade or two (Fry/Osborne 2013: 27).

Having identified these specific parameters, Fry and Osborne begin constructing their methodology, which can be summarized as follows: the likelihood of an occupation being automated depends on to what degree the three different task types are characteristic of that occupation.[7] Fry and Osborne then proceed to categorize jobs according to different occupational characteristics, which they derive from O∗NET – an online service developed by the US Department of Labor. This database provides information on occupational work activities and defines the key features of an occupation, allowing the authors to:

> a) objectively rank occupations according to the mix of knowledge, skills, and abilities they require; and
> b) subjectively categorize them based on the variety of tasks they involve (Fry/Osborne 2013: 28).

In cooperation with machine learning experts, they "subjectively hand-label" 70 occupations[8] by "eyeballing" the O∗NET job descriptions and answering the question "Can the tasks of this job be sufficiently specified, conditional on the availability of big data, to be performed by state of the art computer-controlled equipment [sic!]" (ibid.: 30). The automatability of a wide range of tasks within a given occupation is examined, with occupations being assigned a 1 if they are categorized as automatable and a 0 if not. The majority of jobs categorized by this method are assigned either a very high or a very low automatability (see: Appendix, Table 1).

[7] For example, a dishwasher requires a lower degree of social intelligence than a public relation specialist, rendering his occupation more susceptible to automation.

[8] The specific occupations were chosen based on how confident the experts were in their labelling. The experts rated their confidence in the classification of these 70 occupations as "high".

The lack of a standardized categorization system is attributable to the fact that the job descriptions in the O∗NET database are particular to each occupation. The subjective labelling of these occupations represents an improvement on previous attempts to create objective rankings, which yielded some questionable results.[9] Fry and Osborne proceed to extrapolate this subjective classification for the remaining 632 occupations. First, they compare nine objective attributes of a certain occupation, which are related to engineering bottlenecks (e.g.: manual dexterity, social perceptiveness), to the subjective classifications of the 70 original occupations. Second, a probabilistic model is used to examine the relation between bottleneck-related attributes – i.e., automatability indicators – and the automatability of any given occupation. Finally, they match this information to the number of workers in each occupation.

Fry and Osborne show that computerization may extend to non-routine tasks in the near future, under the condition that a given task is not subject to engineering bottlenecks. This implies that certain non-routine cognitive and manual tasks, such as legal writing and truck driving, are susceptible to automation, while others, which require creative and social intelligence, are not (ibid.: 43). The findings also distinguish between different levels of risk: high, medium, and low.[10] Their computations place 47 percent of total US employment in the "high risk category" – are i.e., "jobs that potentially automatable over some unspecified number of years, maybe a decade or two" (ibid.: 44).

3.2 Arntz et al. and the task-based approach

[9] In 2009, Blinder and Krueger utilized a similar methodology in order to determine the "offshorability" of certain occupations. However, the attempt to create a ranking based on objective task characteristics yielded problematic results, as lawyers and judges were ranked as more "offshorable" than telephone operators and billing clerks.

[10] To be categorized as "high risk" at least 70 percent of the tasks performed by a given occupation have to be automatable.

In their study on the risk of automation in OECD countries, Arntz et al. utilize a so-called “task-based approach” (Arntz et al. 2016: 12). This approach takes into account that the same occupations often have very different task structures, implying that automation will affect workers in the same occupations differently. It is based on a key insight by Autor, Levy, and Murnane (2003) who stipulate that occupations can be viewed as a bundle of tasks. As Fry and Osborne correctly identify, the impact of machine learning on a certain job is a function of its applicability on specific activities. The wide variety of tasks that are bundled within occupation therefore implies that automation will impact those tasks differently. Few occupations consist of completely automatable bundles of tasks.[11] Arntz et al. argue that the impact of computerization on workers will not necessarily depend on the occupation but on the specific tasks. In addition, Arntz et al. address the difficulty in applying the O∗NET data to other countries. They therefore utilize data from the *Programme for the International Assessment of Adult Competencies* (PIAAC) – a unique collection of individual survey data containing detailed information on skills, occupation-related information, occupation-tasks, and competencies (ibid.). This individual level data allows the authors to take two important factors into consideration: a) the reliability of occupational descriptions in predicting workers' *actual* tasks, and b) the comparability of occupations across countries. Arntz et al. then use a statistical model that links the automatability indicators of Fry and Osborne to the occupational tasks derived from the PIAAC data. This procedure rests on the premise that occupations

> with larger shares of automatable tasks are more exposed to automatability than [occupations] with larger shares of non-automatable tasks (Arntz et al. 2016: 13).

The distinction is important because, as mentioned previously, the public debate surrounding the substitution of labor through capital often assumes that occupations will be completely automatable. However, as Arntz et al. show, workers in occupations at “high risk” often perform tasks which are difficult to automate. The challenges facing automation arise from the engineering

[11] Autor et. al (2003) give the following example: In the 1970s and in the US, both truck driving and double entry bookkeeping were tasks performed by a single occupation. Today, computers are responsible for a large portion of the routine bookkeeping but do virtually no truck driving.

bottlenecks as defined by Fry and Osborne. Overall, this approach is less restrictive because rather than assuming that broad occupational descriptions, as found in the O∗NET data, apply to all occupations, it looks at *specific* tasks within an occupation, with a focus on individual job descriptions based on survey data. In addition, it takes into account that occupational tasks in, for example, Germany may differ from those in the US.

Regarding the US labor-market, Arntz et al. conclude that a) the automatability of jobs with high educational requirements and jobs that require cooperation with other employees is lower than the automatability of jobs with a large portion of tasks that are related to exchanging information, selling or using fingers and hands; that b) only 9 percent of total US employment face a high risk of automatability; and that c) *using individual level information leads to significantly lower predictions of occupational automatability* as well as less extreme values in the distribution of automatability (see: Appendix, Table 2).

Regarding Germany's labor market, Arntz et al. find that 12 percent of occupations can be placed in a "high risk" category (Arntz et al. 2016: 15). Similar numbers can be found in a study conducted by Dengler and Matthes (2015). Their methodology introduces a "substitution-potential" which categorizes the tasks *necessarily* – not sufficiently – required to perform the occupation as either "substitutable" or "not-substitutable". The number of substitutable tasks is then divided by the total number of *necessary* tasks for any given occupation. The influence of a specific occupation on the aggregate automatability of the entire labor-market is weighted according to the number of employees employed in that occupation. Dengler and Matthes place 15 percent of all jobs in Germany in a "at risk" category and, similar to Arntz et al., find a lower polarization in the distribution of automatability (Dengler/Matthes 2015: 3). While they find that the substitution-potential decreases for jobs with higher educational requirements, there are virtually no differences in the automatability of occupations without vocational training requirements compared to occupations that require at least two years of vocational training (ibid.: 4). The reason for this is that many of the tasks performed by workers without vocational training, such as washing the bodies of nursing home patients, are difficult to translate into an algorithm.

An example illustrates the explanatory power of the task-based approach: According to Fry and Osborne, retail salespersons face an automation potential of 92 percent. This is because Fry and Osborne view only a limited set of bottleneck-tasks of highly automatable jobs and apply these to the *average* task descriptions of other occupations. During this process, the wide range of tasks actually performed by individual workers is reduced to those performed by all workers on average. However, based on the PIAAC data only 4 percent of the people working in that occupation can perform their jobs without group work or face-to-face interactions. Group work or face-to-face interactions fall under the bottleneck-category of social intelligence, meaning that this aspect of the occupation is difficult to computerize.

The second part of the analysis by Arntz et al. is dedicated to the issue of comparing occupations in different countries. Their data suggests that individuals in the same occupation perform different tasks depending on which country they work in. Two explanations are given: a) national differences in the organization of the workplace, and b) differences in the adoption of new technologies (Arntz et al. 2016: 17). For example, occupations in country A may rely less on interpersonal cooperation and face-to-face interactions than country B. In certain countries, such as Italy and Germany, occupations are characterized by a lower share of communicative tasks, whereas occupations in the US and UK tend to be more communicative and therefore less susceptible to automation. Assuming that there are little to no differences in the workplace organization of both countries, the automatability of occupations in country A might still be higher than in country B, because country A invests more resources in the research and implementation of new automation technologies. This also implies that occupation in countries which already exhibit high levels of automation have a lower potential for automation.

In sum, the findings by Arntz et al. show that the potentials for automation are often overestimated by occupational-level studies. Not only do different approaches lead to significantly different conclusions about the automatability of jobs, but there are also factors that make cross-country comparisons difficult. While one could argue that future advancements in artificial intelligence might lead to solutions for the current engineering bottlenecks that are preventing non-routine tasks from being automated, these predictions are likely to be of a more speculative nature. The problem with the article by David Precht, which was mentioned in the introduction, is that it misleads its readers and does not fully encapsulate the ongoing debate. It contributes to public fears rather than providing a more nuanced picture of how automation will affect employment in the future.

4. Predicting the effect of automation on employment

There are still more caveats that need to be taken into consideration when predicting how automation will affect employment. The estimated automation potentials by Fry/Osborne and Arntz et al. only capture whether an occupation, given its current task structure, could *theoretically* be replaced by a machine or not. There are a few additional reasons why automation potentials should not be equated to actual job losses. For the sake of brevity, this chapter will discuss the following reasons:

a) technological diffusion (the gap between the potential and the actual implementation of a certain technology), and
b) induced job creation (the creation of new jobs due to technological changes).

4.1 Technological diffusion

Solow's Paradox postulates that the effect of the computer age on the economy can be observed everywhere but in the productivity statistics (Triplett 1998: 1).
According to Brynjolfsson et al. (2019), we are currently experiencing a comparable situation with newer technologies. On the one hand, there are astonishing examples of new transformative technologies, such as artificial

intelligence, which already surpass humans in selected tasks and could greatly increase productivity. However, over the past decade, productivity growth in most OECD countries has decelerated significantly (Brynjolfsson et al. 2019: 1). Economic gains have been unevenly distributed, leaving large segments of the working population in advanced economies with stagnating incomes, declining metrics of well-being, and good cause for concern. Brynjolfsson et al. argue that the main contributor to this contradiction is the slow implementation of AI technologies, causing the adoption of AI to severely lag behind its technological capabilities. The slow *diffusion* of AI into the general economy can be explained when viewing AI as a General-Purpose Technology (GPT). GPTs can be characterized as follows:

a) they are pervasive (i.e., the have the ability to spread to most sectors),
b) they improve over time, and
c) they enhance the possibilities for further technological innovations, allowing new products and processes to be invented and produced.

GPTs often diffuse over longer periods of time. For example, computers took 25 years to "reach their long-run plateau of 5% of nonresidential equipment capital" (Arntz et al. 2019: 7). Other examples include the steam engine, electricity, and the internal combustion engine. What all these technologies have in common is that they achieved widespread productivity gains and adopted only once a sufficient stock of new technology is built and other necessary complementary investments have been made (Brynjolfsson et al. 2019: 10). Furthermore, firms can be reluctant to adopt such technologies, since GPTs tend to be costly, take time to implement, and their success and impact on productivity growth is difficult to measure. Arntz et al. (2019) find that older technologies will still dominate the production processes in German firms, despite the shares of capital based 4.0-technologies having roughly doubled over the past decades. In fact, many firms are still upgrading from 1.0/2.0 to 3.0 technologies,[12] rather than introducing newer ones (Arntz et al. 2019: 7).

[12] Arntz et al. distinguish between 1.0/2.0-technologies, which are "manually controlled technologies that are either functioning mechanically or electrically, but are not IT supported",

There are several factors that impact the speed at which 4.0-technologies diffuse into the general economy. First, the speed of diffusion hinges on whether automation technologies can execute select tasks at lower costs than workers. This highlights the, perhaps obvious, fact that the profitability of new technologies is more important to firms than theoretical automation potentials. Hence, the speed of diffusion in the future will depend on the cost of labor and wage setting institutions such as unions and minimum wages. Labor at the lower end of the wage-scale may therefore be shielded from automation more than workers in the middle of the wage distribution (Arntz et al. 2019: 8).

Second, additional complementary investments are required to make GPTs profitable, such as organizational restructuring and the acquisition of new workers with the right skills (Brynjolfsson et al. 2018: 6). A shortage of qualified personal that can handle 4.0-technologies may slow the introduction of new technologies. These risks form a major barrier to the implementation of 4.0 technologies, as is evidenced by the findings of Arntz et al. (2018). They find that 65% of German firms were reluctant to invest in 4.0-technologies between 2011 and 2016 because of these considerations.

Last but not least, there are important ethical considerations that already limit the speed of technological innovation. A well-known example is the autonomous car, which bears numerous legal obstacles regarding, for instance, the question of liability in case of an accident.

In sum, these two stories – namely the simultaneous advancement and the slow implementation of 4.0-technologies – are not contradictory. Instead, they suggest that our economies are entering a phase of transition. However, it will require a combined societal effort to realize the benefits of AI through the restructuring of our production processes. Furthermore, it remains unclear how

3.0-technologies, which are technologies that are supported by computers and software algorithms, and 4.0-technologies, which are fully IT-integrated and require intervention only in the case of failures (Arntz et al. 2019: 7).

labor, new production processes, and business models might complement new AI technologies in the future.

4.2 Induced job creation

The introduction of automation technologies does to some extent replace workers. However, there are certain compensating mechanisms that counteract the initial displacement effect. First, there is the *productivity effect*. An analysis of Acemoglu and Restrepo (2018) stresses the central role of the productivity effect on both wages and employment. According to their observations, the technologies that may reduce the demand for labor are not those that are highly productive, but rather those that are “just productive enough to be adopted” (Acemoglu/Restrepo 2018: 9). Automating tasks makes firms more productive, reducing costs and prices, and raises the quality of existing products or enables new types of products or services to be made. These effects lead to an increase in demand and production, with the economy expanding and the demand for labor rising in sectors that have not adopted new technologies (multiplier effect). On a microeconomic level, the productivity effect can cause less productive companies to go out of business and more productive companies to grow, ultimately resulting in no net change in employment. Second, there is the *reinstatement effect*. This effect impacts the labor market in two mutually complementary ways: a) new technologies allow new tasks to evolve in which labor has a comparative advantage, and b) the displacement of workers increases the amount of labor, allowing new, more productive tasks to be performed (ibid.).

Ultimately, the net effect of automation on employment remains an empirical question. A study by Gartner und Stüber (2019) on the effect of automation on the German labor-market finds that between 1976 and 2017, the loss of jobs due to technological change was fully compensated by the creation of new jobs. Despite the increased automation of many tasks in the German industry, new tasks have sprung up either in the same economic sector or in other non-related economic sectors (Gartner/Stüber 2019: 4). In fact, they find that the rate at which old occupations are being replaced by new ones has decreased since 2005 in relation to the 1990s, suggesting that the speed at which job loss is occurring has slowed down. However, they also find that workers are impacted differently depending on their educational attainment. Low-skilled workers are particularly exposed to automation and the demand for low-skilled labor has been steadily declining in Germany. Highly educated earners are least exposed to being potentially automatable and the demand for high-skilled labor has increased in Germany (ibid.: 5). Further differentiating the results, the number of middle-income occupations requiring vocational training has slightly declined and the turnover-rate at which low-skilled jobs are replaced by other low-skilled jobs is higher than those of more skill-based occupations. Gartner and Stüber conclude

that technology-induced unemployment is largely caused by mismatches in both the educational attainment of workers and the educational requirements of the new occupations, suggesting that policies which focus on retraining and education will becoming increasingly important in the future.

5. Conclusion

The findings of this paper provide a more nuanced context for the future of employment and 4.0-technologies. The first chapter has shown that concerns about technological unemployment are not new and that while displacement is a bitter reality for those affected by it, the fears of mass automation have proven to be unwarranted in the past. The second chapter argues that this might not hold true for the future, that the differences in the calculations of automation potentials can be explained by different methodologies, and that automation potentials tend to be overestimated in public debates. The third chapter showed that there are a number of factors that influence the implementation of 4.0-technologies and predictions of technology-induced unemployment. Automation cannot be equated to the substitution of labor with capital. Instead, new transformative technologies may complement labor in a number of ways, freeing up labor, creating new jobs, and increasing the demand for high-skilled labor. A final aspect that should be considered is that we as a society can influence these developments. We may have strong preferences for the continued provision of certain tasks and services by humans, such as nursing or caring for the elderly. Hence, even if automation will increasingly complement certain occupations in the future, humans will preserve their comparative advantage in performing certain tasks.

6. Appendix

Table 1 (p. 10):

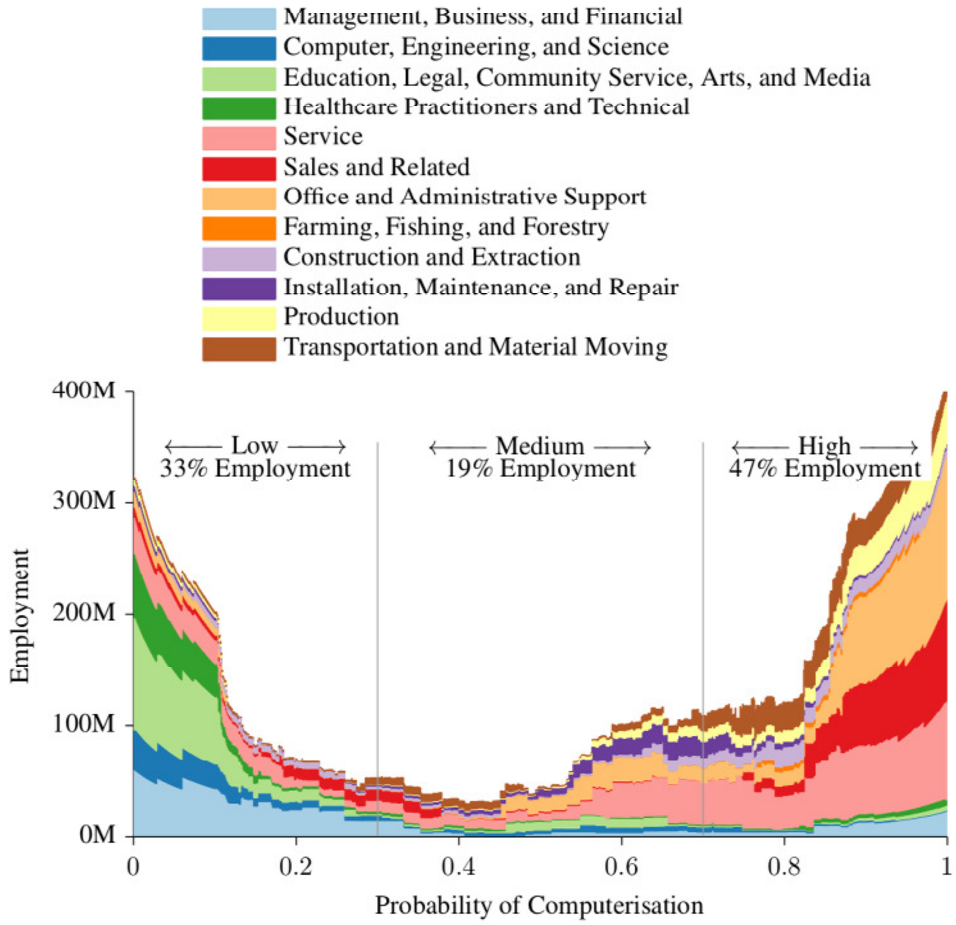
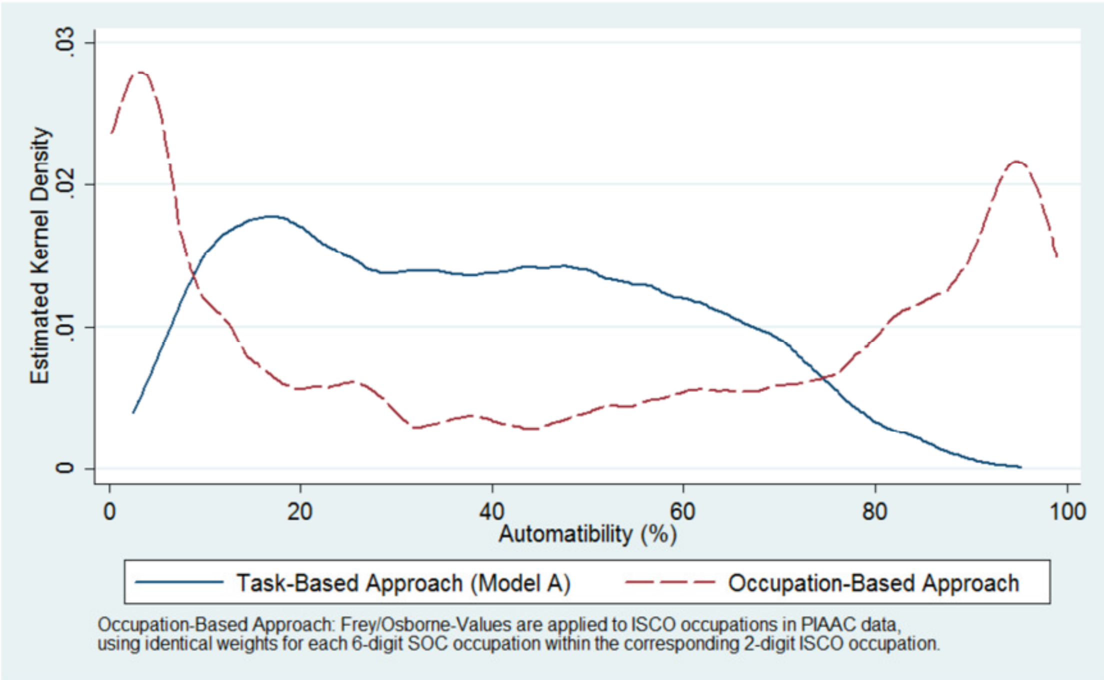


FIGURE III. The distribution of BLS 2010 occupational employment over the probability of computerisation, along with the share in low, medium and high probability categories. Note that the total area under all curves is equal to total US employment.

Source: Frey, Carl Benedikt/Osborne, Michael A. (2013): The Future of Employment: How Susceptible Are Jobs to Computerisation?, online at: https://www.oxfordmartin.ox.ac.uk/downloads/academic/The_Future_of_Employment.pdf, September 2013, [accessed: 13.2.2021]

Table 2 (p. 13):



Source: Arntz, Melanie/Gregory, Terry/Zierahn, Ulrich (2016): The Risk of Automation for Jobs in OECD Countries: A Comparative Analysis, OECD Publishing, Paris.

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