Aalto University
School of Business

The Effects of Technological Changes on Employment

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Teo Hova

Aalto University School of Business

Department of Economics

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Instructors: Pauli Murto and Mikko Mustonen

Opponent: Rosa Nylén

Abstract

In this Thesis, I study the effects of Technological Changes on employment in a literature review. I present the features technological changes have and how human labor and technology interact in the labor markets. I will answer the question if technological changes cause unemployment by studying David Autor and James Bessen's models on worker's skill acquiring decision within occupations and the theory of industry and occupation-specific demand elasticities. The models viewed in this Thesis are quite mathematical but they will offer a decent insight on the labor force behavior. The theory behind industry and occupation-specific demand elasticities is definitely abstract but it manages to explain the main effects of occupation and industry-specific matters on technology affected employment. Finally, I present an outlook of the effects that the digitalization might have on employment.

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1. INTRODUCTION

Since the invention of the wheel, humankind has known the phenomenon called Technological Change and through that the definition of 'technological unemployment' (Woirol, 1996). This indicates the fact that human race has always been concerned about the effects of rapidly developing technological changes on their employment. The concern has not been any frivolous opinion due to the reality that technological changes in manufacturing truly have substituted or eliminated certain occupations or tasks previously done by humans. According to Autor (2015), the relative share of US workforce employed in agriculture decreased from 41 percent to 2 percent during the years 1900-2000, due to technological development including e.g. automated machinery. In addition, Autor (2015) states that this was not the first time technology caused unemployment in the history of humankind. A more famous example of unemployment caused by technological change is an incident where English textile workers protested new automation machinery in their factories due to job losses in the early 19th century. These examples imply that the humankind has been at least cautioned towards technological changes related to their occupations. Many labor economists have studied the case of technological change's effects on employment (see e.g. Autor, 2003; Bessen, 2015; Brynjolfsson, 1998; et al.) in the last decades due to the fact that the technology is developing in a rapid and exponential pace.

In this thesis, I answer the question if technological development will cause unemployment in the long-term. My purpose is to create a whole ensemble of theories, which unites earlier research related to this case in order to produce a significant thesis on the effects of technological development on employment and an outlook of the upcoming digitalization's effects on employment. As the most significant resources for this thesis I used articles and research that are studied by recognized authors and include widely approved theories such as Daron Acemoglu and David Autor's Handbook of labor economics, Chapter 12, Skills, tasks and technologies: Implications for employment and earnings, David Autor's article Why

Are There Still So Many Jobs? The History and Future of Workplace Automation, James Bessen's study papers Automation and Jobs: When Technology Boosts Employment and How Computer Automation Affects Occupations: Technology, jobs, and skills and Erik Brynjolfsson's & Andrew McAfee's The Second Machine Age. I found it consistent for this thesis to be a literary review because the subjects wielded are well studied and with the information produced in the past, I am able to combine earlier results into a wholesome thesis. In order to study the case of technological unemployment further we need to define what the phenomenon called Technological Change means (Chapter 2) and what are its effects on employment (Chapter 3). The fourth chapter presents an outlook of the effects of digitalization after which in Chapter 5, an overview of the results of the effects caused by technological change is presented.

2. TECHNOLOGICAL DEVELOPMENT

Technological development, or change, is "a loose concept that has multiple meanings. The concept originates in the 1930s from issues concerning unemployment due to technology. It was subsequently applied to the study of economic growth, namely productivity" (Godin, 2015). As Godin states, there has been a discussion considering technological development and unemployment at least since the 1930's which indicates the fact that human race is, and has been, concerned about the effects of rapidly developing technological changes on their employment. Although technology is developing rapidly, not all new inventions benefit the human society – or in this case, not all inventions are an advantage to save labor e.g. Microsoft Office Assistant[1]. Additionally, technology has its limits considering the pace of development. Yet, to accomplish growth, new ideas and new ways of working are needed. In this chapter, I focus into the theory behind technological change.

2.1 GROWTH THEORY – WHY DO WE NEED TECHNOLOGICAL DEVELOPMENT

Productivity is the main reason why more powerful and labor saving technologies are created due to economies' and corporations' goal to gain more output with the same input in order to reach better living standards and profit[2]. In economics, productivity growth is usually measured by labor productivity which practically speaking means output per worker. When measuring the productivity in growth accounting, the causal Cobb-Douglas production function is primary used:

$$\frac{Y}{L} = A^{\frac{1}{1-\propto}} \left(\frac{K}{Y}\right)^{\frac{\propto}{1-\propto}} h.$$

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[1] Microsoft Office Assistant "Clippy" was a virtual office assistant for computer users. The users experienced it useless and annoying leading "Clippy" to be left out from future computers.

[2] Consider the production function $Y_t = F(K_t, L_t, H_t, A_t)$ where F represents the ways of combining factors K, L, H and A. Y is the result of these factors combined in a productive way.

Y/L stands as the output per worker also referred as labor productivity, A stands as the total productivity (level of technology), K/Y corresponds as capital coefficient and h as the human capital. The exponent α is the elasticity of total production to capital. According to the theory of growth accounting, the capital coefficient K/Y is a constant in order to achieve stable growth, meaning that an increase in capital will not have an impact to labor productivity in the long-term. The idea behind this model comes from a Nobel rewarded economist Robert Solow, who replaced the old linear production function with a nonlinear function due to the fact that the linear function did not regard declining marginal productivity. The problem with the linear function was that it assumed technology to be a constant and the only way for gaining growth was by gaining capital. As seen in the equation, when the capital coefficient K/Y is a constant, the only way to gain growth is now by increasing variables A and h, total productivity and human capital. According to Pohjola (2017), three quarters of labor productivity came from total productivity during the years 1950-2014 in the US and the corresponding amount in Finland was two thirds of the labor productivity. Pohjola's statement indicates the fact that technological development is the main source to gain productivity growth and through that profit growth.

However, as said in the beginning of this chapter, not all new ideas benefit economies and corporations or in other words, not all new ideas increase the total productivity. According to (2011), the new ideas should meet the criteria of being pervasive, improving over time and being able to generate innovations. When the new idea or technology meets these criteria, the ideas are called General Purpose Technologies (GPTs). According to Gordon (2012), the most remarkable GPTs in the economic history are steam engine and electricity since it took approximately 100 years for these inventions' full effects to convey to the economy, meaning that these ideas improved over time and generated new ideas for one hundred years. Even though GPTs are important for economy to grow, inventing one pervasive and innovation-generating idea is not a durable solution. The GPTs tend to face a

problem related to their versatility due to the fact that although they are multipurpose and scientists are able to invent new ways to utilize them, at some point the river of new ideas will drain. For instance, before the invention of steam engine, productivity had not grown in four centuries. Eventually, the introduction of steam engine and electricity boosted the economy to an unprecedented rise. However, in the 1970's the boost started to slow down and productivity growth became slower (Gordon, 2012). The season of slow growth continued until 1996, when the so-called Third Industrial Revolution emerged and started to heal the economy. The third industrial revolution entailed computers, the web and mobile phones for instance, but the intriguing thing was that the computers etc. were already introduced in the 1970's. This phenomenon implies that a clear lag appeared between the introduction of computers and the boost they gave to the economy (Brynjolfsson & McAfee, 2014). This feature that GPTs tend to have is called Productivity Paradox, meaning that when a new GPT is introduced, it might take decades for their full effects to convey to the economy (Brynjolfsson & Hitt, 1998).

2.2 PRODUCTIVITY PARADOX

In 1987, Morgan Stanley's chief economist Steven Roach drew attention for the first time to the productivity paradox in his study "America's Technology Dilemma: A Profile of the Information Economy." In his study, he endeavored to find the reason behind slowed down productivity growth in the US since 1973, and his conclusion was that even though the amount of computers had substantially increased in workplaces, they had very little effect on economic performance (Brynjolfsson & Hitt, 1998). Albeit companies were investing on computers, the common belief was that they did not contribute to productivity, and on the other hand, the investments were also proportionally small compared to other investments such as capital equipment (Brynjolfsson & Hitt, 1998). One of the premier researchers of technological change, economist Zvi Grilichies, paid attention to this dilemma and

he stated in 1996 that there are systematic biases in the measurement system of productivity growth that prevent an accurate assessment. According to Brynjolfsson and Hitt (1998), traditionally most productivity metrics are oriented around counting resources, such as workers and customers and as long as the investments in IT, such as computers, allow companies to operate at lower costs, the traditional metrics work fine.

From Grilichies statement, Brynjolfsson and Hitt (1998) found three underlying reasons for poor productivity growth in IT investments. Firstly, the measurement metrics should include such things as product quality, customization and other intangibles which IT tends to have and in addition, the input metrics should contain quality and quantity of capital equipment and materials together with organizational capital and training and education of the workers. The third reason for poor productivity growth they found was that the organizational structures companies have might not endorse the new technology. The conclusion from Brynjolfsson and Hitt's findings is that even if companies invest in IT, it does not increase productivity immediately or not necessarily at all. The organization itself needs changes too in order to gain profit from the investments and to avoid the biases in the statistics.

2.3 MAN AGAINST THE MACHINE

Even though it is important for companies to invest in GPTs such as Information Technologies in order to retain competitiveness in the markets, nowadays it requires continuous monitoring of technological development. In 1965, co-founder of Intel and Fairchild Semiconductor Gordon Moore made a discovery about the pace of technological development explaining that the pace of technological change was exponential. He noticed that as the transistors Intel used in their computers got smaller, the company was able to increase the computing power of computers exponentially because more transistors fit into one integrated circuit. In 1975, this exponential growth rate of computing power was entitled as Moore's Law and the

computing power was projected to double every two years (Moore, 2006). Although Moore's Law is widely accepted and trusted, there has also been evidence against it. Brynjolfsson and McAfee (2014) state that Moore's Law has its limits related to the laws of physics, meaning that the amount of how many electrons can travel through one integrate circuit per second and how much faster information can travel through fiber-optic cable is finite. These statements indicate that Moore's Law must at least slow down at some point, which has already become reality since according to The Economist Technology Quarterly (September 5, 2015) Intel has faced troubles with doubling computing power every two years. Moore himself also shared the insight of Moore's Law slowing down as he stated in 2015, that the rate of progress would reach saturation and he would see "Moore's Law dying in the next decade or so."[3]

Despite the evidence on Moore's Law slowing down, the exponential pace of technological change has been profitable for the economy. This insight is shared by Nordhaus (2007), who states that from the year 1850 to 2006, the real costs of labor fell by 1.7 trillion-fold because of technological changes. Even though technology is changing and the cost of acquiring new technologies is decreasing in a rapid pace, human labor is still wanted in the jobs that technological changes cannot handle yet, i.e. the jobs that humans have a comparative advantage and are too difficult to automate (Levy & Murnane, 2004).

According to Autor (2015), the jobs that humans have a comparative advantage in are the ones that demand e.g. flexibility, judgement and common sense because they are the most challenging to automate and we understand these skills tacitly. Autor himself refers this dilemma as Polanyi's paradox, which is simultaneous to another technology-related paradox called Moravec's paradox, which is named after Hans Moravec in the 1980s. Moravec (1988) defines the paradox as "it is

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[3] IEEE Spectrum: Special Report: 50 years of Moore's Law

comparatively easy to make computers exhibit adult level performance on intelligence tests or playing checkers, and difficult or impossible to give them the skills of a one-year-old when it comes to perception and mobility." However, as a disadvantage for human workforce, Moravec's paradox has been partly proven wrong since e.g. driverless cars are already a reality[4], which indicates that more paradox-breaking inventions are coming in the future (Brynjolfsson & McAfee, 2014). For instance, according to Kurzweil (2005), by the year 2020, the computing power of a computer will achieve human brain capacity and approximately, by the year 2045 it will exceed the brain capacity of whole humankind. Consequently, technology might substitute human labor in more skill demanding tasks in the future, if the computing power and skills of robots etc. are as high as human brain capacity and they succeed to have superior skills compared to humans. Despite the evidence against technological paradoxes, the human labor should not be worried about unemployment. In the late 19th century, people employed in the farms were not worried about machines replacing them because no such thing as tractors existed. Since the late 19th century, technology has changed tremendously and yet, there is no shortage on jobs. Nevertheless, technological change has its effects on employment. Otherwise, the concern that technology substitute for human labor would be redundant.

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[4] Google's driverless cars and Sohjoa's driverless busses.

3. THE EFFECTS OF TECHNOLOGICAL CHANGE ON EMPLOYMENT

The supposition is that technological changes substitute for labor – as they intend to do (Autor, 2015). During the last decades, we have invented tremendous amounts of new technologies to save labor. Yet, in the US, the employment-to-population ratio does not seem to reduce (excluding the 2008 financial crisis) which cannot be explained by a decrease in the workforce[5]. This expresses the on-going situation that technological development might substitute or even eliminate certain occupations, but in the matter of fact, its effects on employment are not that certain. Autor (2015) verifies this, as he states that the technological changes have not made human labor obsolete and that the unemployment rate fluctuates cyclically without an apparent long-run increase. The existing grand question among economists and other participants related to this discussion is that does technological change in fact cause unemployment? In this chapter, I try to answer this question by analyzing the occupation and industry-specific influence on unemployment caused by technological change, and by explaining how the technological change is re-forming work.

3.1 THE CHANGE IN LABOR

In the chapter 2, we learned that technology is changing in an exponential pace and new inventions have substituted human labor in the 19th and early 20th century. However, evidence against the substituting progress is presented by Acemoglu and Autor (2011) who state that the changes in technology are assumed to be 'skill biased', due to the fact that the new technologies require more skills to utilize them. This interaction between demand for skills and technological change was first discovered by Jan Tinbergen in 1974 and later studied by Katz and Murphy (1992) and many others. Autor and Acemoglu call this interaction as the 'canonical model'

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[5] See the Appendix

but in other sources, it is widely known as the Skill-Biased Technological Change, SBTC. The fundamental supposition in the model is that in the course of time, new technologies demand more and more skills to use it and in contrast to the early 20th century, these technological changes seems to be complements for skills (Katz & Murphy, 1992).

The effect of technological change benefitting skilled workers was discovered when researchers noticed that income inequalities were growing bigger and technology was rapidly changing in the same time. Greenwood and Yorukoglu (1997) argue that new technologies often require acquiring and processing information and that skills ease this process. Therefore, workers with higher skill level should be rewarded with higher salary in the return to their skills. Milgrom and Roberts (1990) also took part to the discussion arguing that educated workers are given a competitive advantage when information and monitoring costs within firms are decreased by technology, allowing firms to reorganize and workers to perform more tasks. The problem with SBTC seems to be that in the 1970's, fewer people educated themselves to college level and the non-educated – high-school graduates in this case, had better chances to obtain better wages than nowadays. Due to SBTC, since the mid-1960's more people educated themselves due to increase in demand for skilled workers, which led to increased wage rate for educated workers (Figure 1) (Acemoglu & Autor, 2011). This change meant that the wages of the workforce became more unequal – low skilled workers became inferior compared to high skilled workers.

Like many other models, the SBTC model is not perfect because it recognizes only two types of worker levels, high skilled and low skilled. As Acemoglu and Autor (2011) put it, high skilled workers are college graduates or other tertiary level degree graduates and low skilled level workers are high-school graduates. The model also assumes that high skilled workers and low skilled workers are able to

Figure 1: Detrended changes in college/high-school relative supply and relative wages (Acemoglu & Autor, 2011).

perform in similar occupations and tasks, but the only difference between the two types is that their ability to perform these tasks is different. To understand the idea of increasing wages of high skilled workers better, we can use a generic demand-supply frame. The relation between high skilled workers' wage per low skilled workers' wage is on the vertical axis and the employment ratio for the same variables is on the horizontal axis. When the SBTC affected demand increases, the relation between skilled and unskilled workers' wages increases correspondingly. The demand-supply frame helps us see the interaction between the SBTC affected demand shifts and the increase in wage ratio, which ultimately leads to wage inequality.

According to Acemoglu and Autor (2011), it is critical to the two worker-type model that the high skilled and the low skilled are imperfect substitutes in production. To understand how changes in relative supplies affect skill premia, we need to know the elasticity of substitution between high and low skilled workers. In Acemoglu and Autor's (2011) model, every worker has his or her own set of skills, meaning

that each worker is different. In particular, every low skilled worker $i \in L$ has l_i efficiency units of low skilled labor and every high skilled worker $i \in H$ has h_i units of high skilled labor, and in addition, the model assumes technology to take a factor-augmenting form. The factor-augmentation can complement high skilled workers or low skilled workers since the both types of workers can perform similar tasks. Due to factor-augmenting complementing, the labor markets are vulnerable for skill biased demand shifts. All workers supply their efficiency units inelastically and thereby, the total supply of both worker types can be presented as:

$$L = \int_{i \in L} l_i \, di \quad \text{and} \quad H = \int_{i \in H} h_i \, di$$

The elasticity of substitution between high and low skill workers is in a central role in interpreting the effects of different types of technological changes in the SBTC model. The production function for the aggregate economy takes the following constant elasticity of substitution (CES) form

$$Y = \left[(A_L L)^{\frac{\sigma-1}{\sigma}} + (A_H H)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}},$$

where A_L and A_H are factor-augmenting technology terms and $\sigma \in [0, \infty]$ is the elasticity of substitution between high and low skill workers. (Acemoglu and Autor, 2011) The high and low skill workers are considered as gross substitutes when $\sigma > 1$ and gross complements when $\sigma < 1$. From this model, we can present three key situations. Firstly, when there is no substitutability between high and low skilled workers and thus the output can be produced only by using these factors in fixed portions, the elasticity occurs as zero. Secondly, when the two types of workers are perfect substitutes, the elasticity is infinite and thus there is only one skill both workers possess in different quantities. The third situation is when the elasticity occurs as 1 and the production function inclines to the Cobb-Douglas form, where each factor is paid a fixed share of overall income.

Autor, Levy and Murnane (2003) argued that technological change substitute for occupations requiring only routine cognitive and manual task performing skills and complement the occupations that include non-routine problem-solving tasks, which indicates that the factor-augmenting technological change benefits the high skilled workers relatively more than the low skilled workers. From these statements, we can deduce that the workforce is changing to a more polarized form. The importance of education depends now on the occupation specific matters i.e. the elasticity of substitution within occupations and the factor-augmenting form of technology, which determine the decision of worker to acquire skills or not. In other words, technological change is polarizing the workforce into skilled and unskilled workers, which eventually leads to growing wage inequality.

3.2 GROWING WAGE INEQUALITY

Bessen (2015) states that technological changes improve the efficiency of high skilled labor, leading to larger relative demand for high skilled workers. If we think of this interaction in the generic demand-supply frame again, a skill biased demand shift increases the skilled/unskilled worker's wage ratio, meaning that technological change increases the wages of skilled workers.

To understand the phenomenon behind increasing wages for skilled workers, Bessen (2015) created a model, which explains the interaction between wage and employment. His model follows Acemoglu and Autor's CES model (2011), where every occupation includes a variety of tasks and for each task, k, each worker i produces $A_k s_i^k$ of task output per unit of labor time. In the function, A_k represents the state of factor-augmenting technology and s_i^k measures the skill of the worker at task k. In addition to Acemoglu and Autor's model, k presents also the ability to learn occupation-specific skills on the job. Bessen used computers and their effects to represent technological changes in the model and found that computer usage might lead to wage inequality within occupations. The supposition in this statement is that wage inequality can appear, if the worker's decision to invest in learning new

technology varies with worker skills. If the worker decides to invest in learning, they will demand a rise in the return for skills i.e. higher wages. Let us assume that human capital has a cost, which is paid by either the worker or the firm. The wage in the equilibrium for worker i in occupation j is $w_{ij} = z_j s_i$ and the firm pays workers based on their services, meaning that each worker i earns $p_j a_j s_i$, where p_j is the price of an efficiency unit, a_j is the time it takes worker i to produce a bundle of tasks and s_i is the skill level of the worker. The efficiency unit of occupational service j is

$$p_j = \frac{z_j}{a_j}.$$

When there are only two skill levels and technology can heighten productivity from a^0 to a^1 if worker invests learning cost c, high skilled workers will invest in learning as long as long as the payoff from learning is positive:

$$p^0 a^1 s_{High} - c > p^0 a^0 s_{High}.$$

The high skilled workers will continue to invest in learning until the price falls to

$$p^1 = \frac{z}{a^1} + \frac{c}{a^1 s_{High}},$$

meaning that

$$p^1 a^1 s_{High} - c = z s_{High}.$$

With the new price, the low skilled workers are not willing to invest in learning the skills that are needed in the occupation since their payoff would be negative and thus they relocate to other occupations. However, if the low skilled workers invested in learning, they might stay in the occupation as long as their payoff remains positive and they are able to use the old technology in the occupation. As the new technology emerges, high and low skilled workers' relative wage ratio will increase due to an increase in productivity of high skilled workers:

$$\frac{w_{High}}{w_{Low}} = \frac{p^0 a^0 s_{High}}{p^0 a^0 s_{Low}} = \frac{s_{High}}{s_{Low}} \quad \rightarrow \quad \frac{w_{High}}{w_{Low}} = \frac{p^1 a^1 s_{High}}{p^1 a^0 s_{Low}} = \frac{a^1 s_{High}}{a^0 s_{Low}} > \frac{s_{High}}{s_{Low}}.$$

The results of this model implies that only the skilled workers will now apply to the technology affected occupation and low skilled workers are left with other occupations in which they still have a comparative advantage over technology (Roy, 1951). However, as said in the beginning of this chapter, technological changes substitute for occupations requiring only routine cognitive and manual task performing skills (Autor, Levy and Murnane 2003). Consequently, when the low skilled workers apply to these routine and manual tasks including occupations, they might encounter technological challenges in these occupations too. The following chapter will present statements about technological change related to industry and occupation-specific matters.

3.3 THE INFLUENCE OF OCCUPATION AND INDUSTRY-SPECIFIC MATTERS ON EMPLOYMENT

According to Bessen (2017), the US textile and steel industries employed over 300 and 500 thousands people respectively in 1958. By the year 2011, the numbers decreased to 16 and 100 thousand. Rowthorn and Ramaswamy (1999) argue that technology and changing demand were the primary reasons for the decline. Meanwhile, in non-manufacturing industries such as service industries, the change in employment rate stayed positive. This can be seen in Figure 2 that presents the occupational percent changes in employment from 1979 to 2009. One explanation for the differences in manufacturing and non-manufacturing industries' employment is that the effect of technological changes is more positive in non-manufacturing industries (Bessen, 2017). It is important for us to understand the factors that determine whether technological changes have a positive or negative effect on employment in a certain industry.

Figure 2: Percentage change in employment by occupation, 1979-2009 (Autor, 2015).
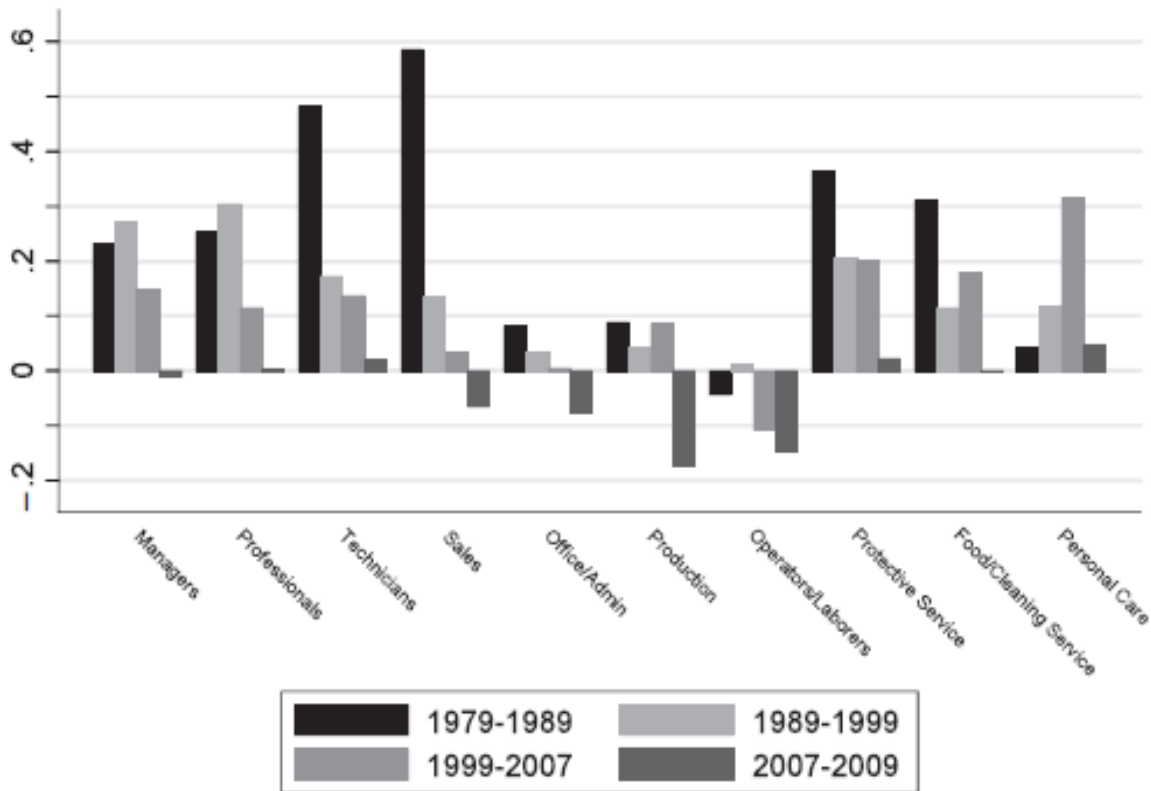
3.3.1 INDUSTRY-SPECIFIC MATTERS

According to Bessen (2017), the most pivotal factor in understanding the industry-specific unemployment caused by technological changes is the product demand of an industry. Bessen states that technological changes increase labor productivity allowing firms to produce more output with the same input, meaning that the supply curve moves to the right. Increased supply lowers the market prices, ultimately offsetting the effect of technology that saved labor, if the product demand is elastic. After a couple of centuries of rapid productivity growth in manufacturing industries, the product demand became relatively satiated and inelastic meaning that new improvements in production led to decline in employment. In addition to product elasticity, income elasticity also had its effects on employment in manufacturing industries. The products of manufacturing industries were already

proportionately old and considered as inferior goods. By the 21st century, people earned relatively more compared to the 19th and 20th centuries meaning that the inferior goods had a very low income elasticity and thus low demand. In contrast, the new products of non-manufacturing industries such as services were luxury and combined with high initial prices and production improvements the non-manufacturing industry's employment grew.

Bessen's model gives us a good explanation why the employment reacts differently to technological changes in different industries. In new industries, production improvements increase employment due to high demand elasticity and high initial prices in contrast to old, more mature industries where demand elasticity is low and an increase in supply does not have the same affect. Even though the model explains the effects of industry-specific matters on employment, it leaves ignorance on which occupations within industries are in danger to be substituted by technology.

3.3.2 OCCUPATION-SPECIFIC MATTERS

To understand which occupations were in danger to be substituted by computerization in the US, Frey and Osborne (2013) created a model to explain this, which can be seen in Figure 3. They found out that 47% of the employment was in high risk of being substituted by computer automation, 19% in medium risk and 33% of employment was in low risk category. The results suggests that the generality of the occupations included to high-risk category were occupations that require only routine and manual task performing skills such as office clerks. Surprisingly, most of the people working in sales occupations were also ranked to the high-risk category although sales occupations in overall require non-routine skills and common sense. The medium-risk category includes occupations that require pattern recognition and perception such as bus drivers and construction workers. Occupations that are involved with leadership, education, humanities and computer science were listed in the low-risk category, which means that these

occupations are the hardest to automate. Frey and Osborne's (2013) results aligns to Autor, Levy and Murnane's (2003) insight that humans will have a comparative advantage over technology in the occupations that requires social skills, non-routine and common sense, i.e. the occupations that are too hard to be automated yet.

However, Frey and Osborne's (2013) study does not commit oneself on which occupations can benefit from technological changes. Bessen (2015) states that there are at least two reasons why technological changes can increase the demand for a certain occupation. Firstly, due to technological changes the firms can operate at lower costs, which eventually lowers the market price of products. This results in increased demand and thus increased demand for labor. Secondly, because technological changes increase the efficiency of labor in an occupation, relatively more labor can be demanded from that occupation compared to others.

Figure 3: The Distribution of Occupational Employment of Total US Employment over the Probability of Computerization (Frey & Osborne, 2013).
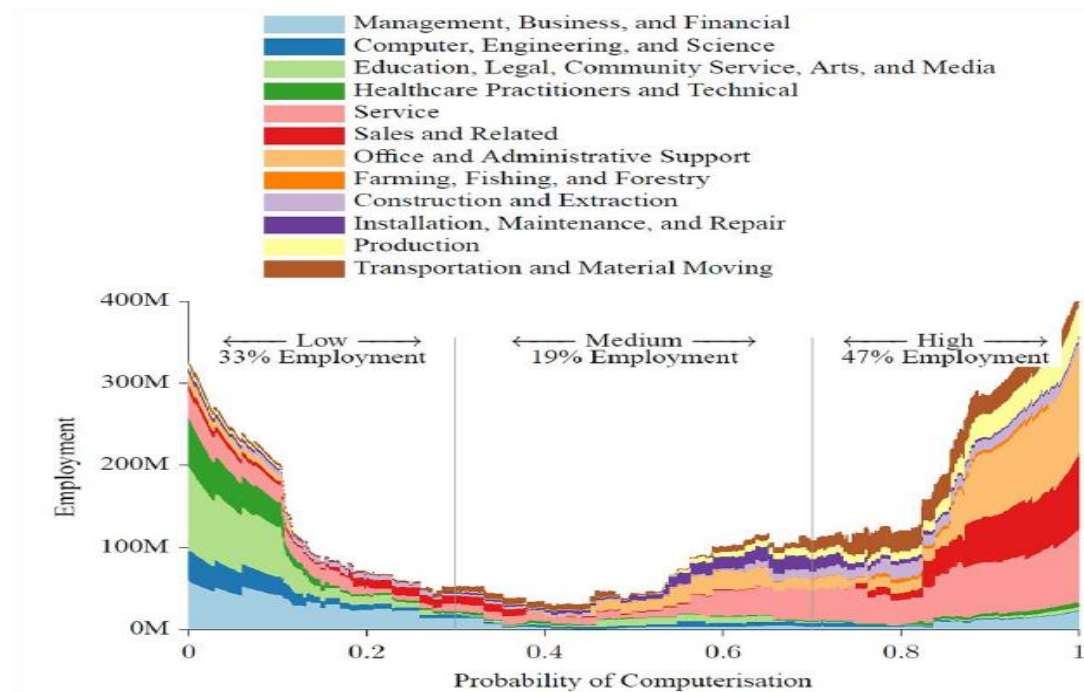
In other words, firms can substitute labor in the automated occupation for labor in other occupations. The loss of jobs in one occupation can thus increase employment in another occupation within firms. Frey and Osborne's research gives us information on the probability of computerization within occupations in a *ceteris paribus* form. Nonetheless, the reality is that technology is changing and the new era of technological changes is transforming the way work is done and merging the world in an unprecedented way.

4. NEW ERA OF TECHNOLOGICAL CHANGES

The earlier chapters in this Thesis have concentrated merely on the effects of automatization, robotization and computerization, i.e. the technologies of the past and present world. More interesting questions for us are yet to know what the future trends of technological changes are and what are their effects on employment? One trend of technological changes that society has already observed is digitalization. The divergence of digitalization compared to earlier technological changes is its non-mechanicality, since automation and computerization needed fixed capital to emerge, the inventions of digital era are based more to Information and Communication Technology (ICT).

According to Khan (2016), digitalization is a process where analogical information is transformed to numeric and binary form within industries. The process of digitalization has enabled e.g. blockchains and Big Data to our utilization, which are remarkably different inventions compared to mechanical inventions since they do not require new fixed capital to utilize them – instead we may use already invented IT capital. Eichhorst (et. al. 2016) describes the new non-mechanical era of inventions as "platform economy", meaning that the suppliers of inventions offer their goods and services through a professionally organized internet portal instead of selling computers on stores for instance. This phenomenon offers tremendous variation of ideas to utilize, since the available services can be reached online with smartphones without any barriers (Eichhorst et. al. 2016) and in addition, Weitzman (1998) argues that digital technologies provides a massive amount of new means to combine ideas into new inventions. For instance, Uber and Helpling[6] utilize the platform technology to offer services locally, challenging the traditional taxi and cleaning companies to reform their organizations and adapt the digital

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[6] Uber and Helpling are companies that gather individual service producers and customers under the same online platform. The payment transactions are operated by the companies and subtracted by operating costs.

service models too. McKinsey&Company's article[7] verifies this phenomenon stating that as the economic pressure increases due to digital changes, companies in every industry will be affected by digitalization.

According to Brynjolfsson and McAfee (2014), digital technologies meet the criteria of General Purpose Technologies, meaning that digitalization could be the new boost for the dragging economic growth. A report[8], made by a strategy consulting firm Strategy& (2013), reveals that digitalization indeed accelerates economic growth and alleviates job creation since digitalization increased the global economic output by 193 billion dollars and created approximately six million jobs in 2011. This might be just the tip of an iceberg of the economic performance digitalization is able to provide due to the lag in economic performance that GPTs tend to have. The improvement of economic performance surely is not over according to Brynjolfsson and McAfee (2014) who state that the improvement is solely being held back by our inability to process all the new ideas fast enough.

4.1 THE EFFECTS OF DIGITALIZATION ON EMPLOYMENT

According to Eichhorst (et. al. 2016), digitalization is reshaping the forms of employment and work into more flexible and complex ensemble. For instance, working from home and flexible working times are becoming the standard, meaning that the line between career and personal life is becoming more blurred (Eichhorst et. al., 2016). The requirement for more flexible labor within firms is wiping out the traditional concept of full-time job and increasing the amount of part-time work and self-employment. The platform economy is one of the main reasons for the increase in part-time working and self-employment because the suppliers of services and the customers can easily be put under the same platform for a virtual market, meaning

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[7] McKinsey Quarterly, February 2017. The Case for digital reinvention
[8] Strategy& report April 10, 2013. Digitization for economic growth and job creation: Regional and industry perspectives. [Strategy& uses term digitization instead of digitalization.]

that the suppliers – or workers in this case can produce services according to their abilities. According to Eichhorst (et. all, 2016) the new segment of labor has the potential to substitute traditional services in some occupations with wider range of services and flexibility.

The effects of digitalization on employment depend also on the economic level of a country. According to Strategy&'s (2013) report, the increase in employment is greater in developing countries than in developed countries. The reason behind this phenomenon can be explained with the theory of increased productivity. In the developed countries, digitalization affected growth in productivity does not create as much new jobs than in developing countries since the productivity growth merely offsets the technology caused job losses rather than creating more jobs leading labor intensive tasks to offshore into developing markets, where labor is cheaper. On the contrary, in Strategy&'s (2013) report, the increase in employment in developing countries is higher due to three reasons. Firstly, in some countries the digitalization gain is higher than in advanced economies. Secondly, the population of a country might be very large, meaning that minor improvements in unemployment creates a grand number of jobs. Finally, the offshored jobs from developed countries land to developing countries increasing the employment.

As we can see from the statements above, globalization is strongly attached to employment and digitalization. During the last decades, decreased communication costs have been a primary reason in the creation of a global market for products and services (Brynjolfsson and McAfee, 2014). With global markets, firms can acquire labor with the skills they need from anywhere in the world and in the same time the usually low-cost countries can now achieve better wages by applying to work e.g. in the United States (Brynjolfsson and McAfee, 2014). With the effect of digitalization, the idea of global labor markets can be even more drastic because digital technology enables working from home, which means that American firms can hire e.g. Asian workers to work abroad. Globalization together with

digitalization thus creates a competitive and global labor markets with more equal earning possibilities for typically low-cost country workers. According to Brynjolfsson and McAfee (2014), this is good news for overall economic efficiency but not for the countries with relatively high wages since now, these countries face low-cost competition.

5. CONCLUSIONS

In this Thesis, I studied the effects of technological changes on employment. My goal was to answer if technological changes cause unemployment in the long-term. In all truth, technological changes have effects directly on labor force such as the polarization of the labor force and growing wage inequality but occupation and industry-specific matters together with worker's skill level determine the effects of the technology to employment. The effects of technological changes depend on these factors. It is rather irrelevant to make generalizations of the question if technological changes cause unemployment, since the answer is not that uniform.

Nevertheless, technological changes can cause unemployment if the worker possessed low skills and was employed in an industry with mature demand and low income elasticity. The long-term unemployment depends on the ability of the industry – or economy – to generate compensatory jobs. The general comprehension in this Thesis is that technological changes are much skill biased and the workers possessing high skills are more likely to benefit from the technological changes than the low skilled workers. The workers employed in the product elastic industries are more likely to be safe from unemployment since the increased productivity more than offsets the effects of technological changes on employment.

Since digitalization is one form of technological development, it is highly presumable that it has the same effects on employment as other technological changes. In addition, digitalization transforms the traditional 'full time job' work into more flexible and complex ensemble as well as it broadens the labor markets to a global field with intensified competition within labor force. Digitalization also benefits the emerging markets and developing countries more than it benefits the developed countries, in the sense of employment.

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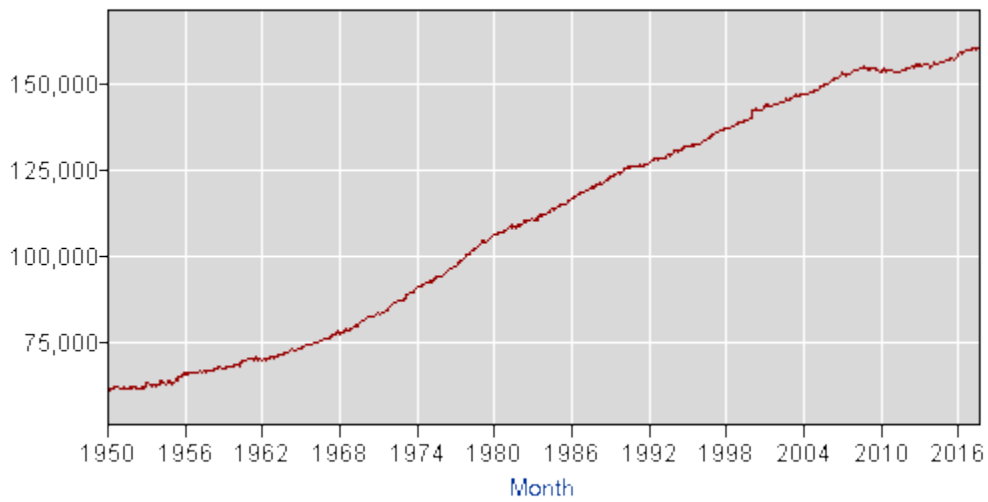
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Appendix
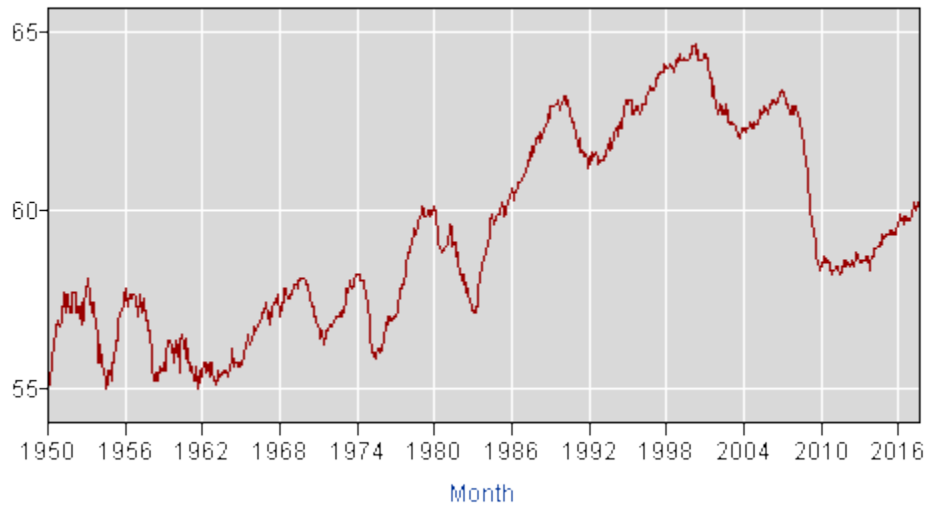
Employment-Population Ratio, 16 years and over.

Civilian Labor Force, 16 years and over, numbers in thousands.