Technological Changes' Effects on Labor Markets



Author: Adam Matias Dong Hoffmeyer Student number: ad4503ho-s Supervisor: Oriol Sabaté Domingo SIMV07, Master's Thesis in Global Studies, Political Science Lund University, May 2019

Abstract

This thesis sets out to illuminate how changes in technological capabilities affect labor markets. Specifically, it compares labor market trends during the last four decades in three Danish sectors; manufacturing, accommodation, and social services. A discussion of these trends is then made against the backdrop of an extensive literature review of research relating to new technologies' effects on labor markets worldwide. Echoing other authors, the thesis recommends a non-deterministic approach to the challenges posed by rapidly changing labor markets focusing less on end-of-work scenarios and more on the important tasks ahead of us associated with restructuring education and reskilling workers holding devaluing skillsets.

Keywords: technological change, automation, labor markets, employment Word count: 19.278 - Blank page -

Contents

1	Inti	oduction	. 1
	1.1	Thesis Outline & RQs	. 2
	1.2	Concept Elaborations for Introduction and RQs	. 3
2	Me	thodology	.5
	2.1	Selection of Reviewed Literature	. 6
	2.2	Categorizations of Reviewed Literature	. 7
	2.3	Why Do a Country-Specific Case Study?	. 7
	2.4	Selection of Case Country	. 8
	2.5	Selection of Focus Sectors	. 9
	2.6	Why Do a Quantitative Analysis?	10
	2.7	Challenges of the Quantitative Analysis	11
	2.8	Methodological Reflections	13
3	The	e literature reviewed1	15
	3.1	Group A: Alarm for Human Joblessness	16
	3.2	Group B: Concerns of Rising Inequality and Changing Skill Compositions but N	ot
	Falling Labor Demand		
	3.3	Group C: Technological Change Creates Increased Human Labor Demand and Prosperi	ty
	3 /	27 Literature Relating to Technological Change's Effect on the Danish Labor Market	22
	3.4	Minding the Gan	35
4	An	alysis – The Case of Denmark	36
	4.1	The Case of Denmark – Introduction	36
	4.2	The Case of Denmark – Sector Specific Comparative Case Studies	46
	4.3	The Case of Denmark – Offshoring	61
	4.4	The Case of Denmark – Concluding remarks	63
5	Dis	cussion and Conclusion6	54
6	Ret	References70	
7	Ap	pendices	30
	7.1	Appendix 1 8	80
	7.2	Appendix 2 8	82

Figures

FIGURE 1 – STRUCTURE OF THESIS
FIGURE 2 – DENMARK, OVERVIEW, 1975-2015
FIGURE 3 – UNEMPLOYMENT/POPULATION-RATIO (AGED 15-64), 1983-2015
FIGURE 4 – DECENNIAL AVERAGE EMPLOYMENT IN DENMARK, ALL SECTORS, 1975-2015 40
FIGURE 5 – AVERAGE YEARLY TOTAL HOURS WORKED RELATIVE, 1975 = 0, 1975-2015, ALL
Sectors
FIGURE 6 – SOME DOWNWARD FORCES ON EMPLOYMENT
FIGURE 7 – EMPLOYMENT IN MANUFACTURING, SOCIAL SERVICES AND ACCOMMODATION 51
FIGURE 8 - HOURS WORKED PER WEEK IN MANUFACTURING, SOCIAL SERVICES AND
ACCOMMODATION
FIGURE 9 – VALUE ADDED IN MANUFACTURING, SOCIAL SERVICES AND ACCOMMODATION 53
Figure $10 - Output$ in manufacturing, social services and accommodation
FIGURE 11 – VALUE ADDED/HOUR IN MANUFACTURING, SOCIAL SERVICES AND
ACCOMMODATION
FIGURE 12 - RELATIVE TFP GROWTH IN MANUFACTURING, SOCIAL SERVICES AND
ACCOMMODATION
FIGURE 13 – JOBS SOURCED INTERNATIONALLY FROM DENMARK
FIGURE 14 – SOME FORCES ON EMPLOYMENT, CONTINUED
FIGURE 15 – COMPARING MANUFACTURING WITH AGRICULTURE

Tables

TABLE 1 – Comparing yearly change rate means in manufacturing & a	GRICULTURE
WITH CHANGE RATE MEANS IN SOCIAL SERVICES & ACCOMMODATION	58
TABLE 2 – INDEPENDENT SAMPLES TEST	
TABLE 3 – SUMMARY, TRENDS IN DANISH MANUFACTURING	

1 Introduction

News outlets all over the world have a story they keep going back to. The main message of this story is, 'The robots are coming to take our jobs'. Both modern and past media have spent thousands of pages and pixels on repeating this concern (Clarín.com, 2018; Cooper, 2018; Jericho, 2018; Kelly, 2018; Shewan, 2017). Scholars too have long been worried that machines could render human work superfluous by causing technological unemployment (Keynes, 1978; Mills, 1938). The debate seems to be picking up steam again as artificial intelligence and advanced robotics are exhibiting ever-more impressive skills. Sources in the debate abound and the opinions are as different as water and fire; from the tech-optimistic hardliners claiming technology will only lead to increased wealth and rising labor demand to the end-of-work'ers preparing their backpacks for a retreated life in the woods.

It is easy to imagine linear progressions of society's development; if technology can do this now, then in 20 years it must be able to do at least this, this and this. More challenging is it to imagine which tasks will need human handling in 20 years' time. However one chooses to formulate the challenges of the debate, it is hard to avoid returning to the complex question, *is this time different*?

To help nuancing our imagination, this thesis sets out to discuss how technological changes can be measured on a macro-economic level and how they affect specific sectors in an industrialized country. An introductory literature review presents recent literature dealing with either 1) how technological advancements has historically affected job markets or 2) how the present wave of technological change will affect labor markets fundamentally different from previous waves. This literature then helps the thesis' purpose of understanding the nuances of the real-life effects of technological change in the case of the Danish labor market.

The literature reviewed uses many names to describe a contemporary boom in technological attainments and applicability. Therefore, it is important to clarify how this thesis uses the different terms. While a fourth industrial revolution associates with broad, general changes in production methods (like earlier industrial revolutions), automation is a narrower concept describing processes where humans are rendered superfluous by new technology. Another related term, the digital revolution, emphasizes the transition from various analogue or mechanical systems to a two-digit system (1s and 0s). In this understanding, the fourth industrial revolution contains processes of both automation and digital revolutions and transitions to digital processes might bring automation of human tasks.

As output of the thesis, a recommendation is made of which indicators should be tracked in order for Danish policy makers to keep an eye on the effects of technological advancements on labor markets. Furthermore, the thesis joins forces with the literature review, and concludes with policy recommendations aimed at softening the adverse effects of a rapidly changing labor market.

1.1 Thesis Outline & RQs

The thesis will be guided by the following research questions:

RQ: How has technological change since 1975 affected (1) the Danish labor market in general and (2) specific sectors in Denmark with high exposure to technological change?

sRQ1: Based on existing theory on the relationship between technological development and the labor market, did the Danish labor market in the period 1975-2015 experience the expected changes related to technological changes?

sRQ2: Which indicators are important to track technologically caused changes on the Danish labor market?

For clarifications of the concepts used in the RQs, see section 1.2.

First, the methodology of the analysis is described in detail in section 2. Then, the literature review presents the literature under study with a focus on the period from 1975 and onwards. This time limitation was chosen, firstly, because this period contains the beginning of a – arguably fundamentally different – new era of technological change where digital information technology changes a broad array

of tasks on labor markets worldwide. Secondly, since the main dataset used, the EU KLEMS dataset provided by Kirsten Jäger (2018), contains data on the period 1975-2015. Thirdly, much of the literature reviewed focus on this period because it is argued that the technological change within this period is of an entirely different character than technological changes experienced earlier in the 20th century.

The thesis then turns to deal primarily with the Danish job market. A descriptive opening section presents a basic overview of the Danish job market including figures showing levels of unemployment, underemployment, and employment by major sectors. Following this, the thesis uses the case of three Danish industries exposed differently to technological change and discusses the labor market trends of these industries. Finally, the thesis discusses which indicators are important to measure regularly in order to track the effects of technological change on the labor market.

1.2 Concept Elaborations for Introduction and RQs

This section aims at helping the reader understand the RQs as detailed as possible.

'Technological change': As companies and institutions invest in new technology, the skills occupied by humans might change as well as the productivity of the work place, often measured as value added per hour worked. In the thesis, the following terms are used interchangeably to essentially refer to this process: technological advancements, innovation, technological developments, and technological progress.

'The labor market in general': A broad term which in this thesis is simplified and boiled down to a handful of indicators namely, among which are number of employed people, productivity, and value added.

'Technological exposure': Sectors relying heavily on machinery and automation processes are assumed to be highly exposed to technological changes while low exposure sectors are sectors where human contact or services are essential. When the word 'exposure' is used in the thesis, it is always referring back to this difference between sectors.

2 Methodology

This chapter discusses the methods applied in the development of first the literature review and then the quantitative case study of Denmark and three focus sectors. An illustration of the structure of the thesis is provided in **FIGURE 1**.

FIGURE 1 – STRUCTURE OF THESIS

Literature Review: Presentation of the debate on automation's effect on labor markets

Overview of the Danish Economy and Labor Market.

Focus on variables relating to GDP, population, unemployment, and changes in sector compositions.

Elaborated discussion of automation's effect on labor markets using the case of Denmark as a showcase to how different sectors respond differently to Quantitative Sector—Specific Inquiry An analysis of key variables related to the discussion of technological change's effect on labor markets. Sectors which are highly exposed to technological change are compared with sectors assumed with low

Results

The case study shows how high-exposure sectors have experienced different trends than low-exposure sectors and reveals which indicators are key to understanding the labor market effects of technological change.

2.1 Selection of Reviewed Literature

The selected topic of this thesis was based on a pilot project conducted in the fall of 2018 at Roskilde University, see (Hoffmeyer & Ma, 2018). This project discusses the effects of technological change on labor markets an OECD-level and contains a literature review which became the springboard for the literature of this thesis. Although some of the same authors are used, the entire literature review of this thesis is unique and written in the Spring term of 2019.

The literature reviewed is categorized, inspired by the pilot project, in groups according to the degree to which the arguments in the literature sounds the alarm for human joblessness and a robotic takeover. Reviewing additional literature, it became evident that a large percentage of the new literature could be placed within these categorizations.

Differently from the pilot project, this thesis has a focus on Denmark. Literature relating to technological changes' effects on the Danish labor market were therefore added in a category for itself.

Among the literature reviewed, one can find articles from academic journals, reports from prominent international institution, reports from private consultancy companies addressed at governments, books by scholars, and a single academic journal note. It was important to the author of this thesis to review a wide array of literature from many different sources to get a nuanced overview of the debate. Prioritizing a wide range of literature meant that the attention to each source became somewhat compressed. It was therefore necessary to put in a focused effort to identify and extract the most relevant arguments from each source. Alternatively, one could have included fewer sources and given each source. Nevertheless, as stated above, it was paramount to the author to exhibit a world-wide debate where the findings depend so much on which regions, countries, sectors, and industries one focuses on.

The search techniques, structure, and operationalizations of the literature review was assisted by the student-guide book by Diana Ridley (2008).

2.2 Categorizations of Reviewed Literature

As Ridley suggests (2008, Chapter 6), one automatically categorizes literature when including it in the review. The author of this thesis therefore chose to make these categorizations explicit and divide the literature in four groups. The categorizations are done solely for the reader, and indeed for the author, to get a sensation of order in the debate. Three of the categories presents literature with various degrees of concern for technological advancements' effects on labor markets and the categorizations are made to highlight these different attitudes. It is important to stress, that some of the arguments included in the literature only indirectly relates to the thesis' focus area but they have been included since they make the foundation for formulating arguments that can be used to support arguments in the different groups of arguments relating more directly with the main topic of the thesis.

Some of the authors' pieces of work could possibly belong in several of the categories and therefore the categorizations must not be taken too literally, but rather as a guiding proposal of ordering the literature. This does not, however, mean that the categorizations are insignificant. The most pessimistic piece of literature in Group A is most definitely incompatible and in disagreement with the most optimistic literature in Group C. The importance given to the categorizations, most thus be balanced. The fourth group of arguments presents literature relating to the case of Denmark.

2.3 Why Do a Country-Specific Case Study?

Focusing on one country involves some limitations. Important national differences between similar economies are automatically excluded from the focus of an analysis which focuses on one country. The pilot project earlier mentioned had an OECDwide focus allowing for analysis of more general trends and comparisons of countries. However valuable that kind of analysis is, the starting point and motivation for this thesis was to gain more detailed insight into the sectoral differences, not national differences, in a specific context. This is not the most detailed level one can choose. In a private mail to the author, David Autor, whose work is among the reviewed literature, mentioned that focusing on the firm-level gave the most detailed insight but also required the greatest resources. The national focus, therefore, became a middle ground where it was possible to focus both on general societal trends and sector-specific differences.

The reasons for during a quantitative case study in the first place were based on an assessment that getting direct contact with data on labor market trends could provide an interesting and rich insight into the real-word effects of technological change. Having an example, the case study, to refer back to is meant to add nuance and legitimacy to the final discussion.

2.4 Selection of Case Country

Many different countries could have been chosen as the focal point of the analysis. Denmark was chosen for a number of reasons. Firstly, it is the country about which the author of the thesis has the best background knowledge on labor market composition and historical changes. Furthermore, Denmark is a country with high productivity rates and with historically important industries in manufacturing and agriculture such as 'beverages' (Carlsberg) and 'medicine production (Novo Nordisk). This means that Denmark is likely to have experienced significant changes in the technologies used in companies and institutions. Moreover, one of the studies included in the literature review reveals that countries with demographic challenges such as ageing populations have higher robot density than other countries. Japan is perhaps the best example of this correlation. Denmark, however, is also dealing with an ageing population having seen the percentage of 65+ year-old in relation to the working age population bump up from 17% in 1960 to 31% in 2017 (World Bank, 2019b).

The combination of the above reasons meant that Denmark could be used as a case with high likelihood of having experienced changes on the labor market related to a changing technological environment. The thesis furthermore limits itself by focusing on Denmark as a whole, without differentiation between rural areas and urban areas for example. Although levels of urbanization certainly have an impact on the local labor markets, the focus needed to be on Denmark as a unit primarily because the datasets used does not break down the countries into regions.

2.5 Selection of Focus Sectors

The selection of focus sectors is an important step in the analysis. Using some of the reviewed literature, the analysis attempts to justify why the chosen sectors were chosen. It was decided that it could enrich the analysis to zoom in on specific sectors with respectively high and low exposure to the changes caused by technological advancements. If one only discusses macro-data, one risks missing crucial nuances in the debate. The skills needed in different sectors differ significantly and since software and machines have only acquired a limited array of capabilities, it becomes paramount to understand the sectors in detail and know which skills are most used in the different sectors if one is to ultimately assess how technological change affects the sector. It must be stated, that the chosen sectors are not the only qualifying sectors in the dataset. There could have been found support in the literature for other sectors too, and these could indeed have been added to the analysis. However, the scope of the thesis encouraged a focus on few sectors.

An alternative to choosing focus sectors would have been to analyze systematically each sector and assign each sector with a score for exposure to technological change. This would have been a quantitative attempt to systematically identify which sectors where most exposed to technological change and which were least exposed. In the end, the focused sector analysis was chosen as it was assessed that a detailed look on a few sectors would add more new nuances to the debate than a general econometric analysis of many variables, industries and sectors – something that is done quite well by other authors (Andersen et al., 2017; Autor, 2015; Autor & Salomons, 2017; McKinsey & Company, 2017).

2.6 Why Do a Quantitative Analysis?

Quantitative analyses give researchers a chance to detect large scale changes over extended time periods and throughout society (Little, 2013). This was exactly what was wished for in this thesis; to gain insight in trends over a 40-year time period in a specific context. Therefore, the main research question of thesis is an open invitation to a quantitative analysis. This, however, is not to say that the research questions could not have been explored differently. Opposed to quantitative work, which according to Creswell & Clark (2017) collects numbers, qualitative approaches, collect words. One could easily imagine a qualitative analysis of the same research question providing rich insights. Interviews with experts of different sectors in Denmark would without doubt reveal diverse and detailed insight into the trends of change experienced on the Danish labor market. Nevertheless, Kirsten Jäger's EU KLEMS database (see section 2.7.1 in this chapter) is a source of data which has not yet been analyzed exhaustively, especially not on a country-specific sector level. Upon discovering Jäger's database, it became apparent that all possible points of interest related to the case of Denmark had not been extracted from the data, neither by Jäger herself nor by Autor & Salomons (2017) and McKinsey & Company (2017) who also use the data. It therefore became a legitimate choice to use the data to enable a deepened discussion of technological change's effect on the Danish labor market. These arguments are the main justifications for choosing a quantitative approach - not due to lacking other methodological options, but because a gap was identified in the detailed quantitative analysis of specific countries included in the dataset.

Finally, is should be noted that the thesis uses complementary data from a number of other databanks to support the analysis, but none of these databanks provide insight in the same detail level of the Danish labor market as the EU KLEMS dataset, which is why this dataset was chosen as the main input of primary data.

2.7 Challenges of the Quantitative Analysis

The quantitative analysis of this thesis faced some challenges relating to variable selection and data scarcity. As a perfect proxy indicator for technological change does not exist, a range of variables were instead included in an attempt to control for as many non-technology related factors as possible. Making sense of the resulting puzzle was difficult as some of the pieces needed were non-existing and some of the pieces on hand were 'damaged' by only covering short time periods. These challenges in combination mean that the thesis is focus on putting forth 'qualified estimates' on technological change's effects on the Danish labor market. In section 4.4 of the analysis, the blind angles of the quantitative analysis are further discussed.

2.7.1 Selection of Database

The main source of primary data in the thesis is the EU KLEMS dataset. The EU KLEMS database is referenced as wished by the author, Kirsten Jäger, in the following way: (Jäger, 2018). It is by far the most comprehensive database on European productivity and labor market compositions and is used repeatedly in the literature reviewed (Autor & Salomons, 2017; McKinsey & Company, 2017). The database is not perfect though. For example, it lacks information about total factor productivity growth from 1975 to 1996 in many of the countries included (also Denmark) as Jäger could find no data on certain variables in Eurostat or European National Statistical Institutes before 1995 (Jäger, 2018).

The EU KLEMS database is the database which provides the most variables and goes most in detail on the sector and sub-industry level. The database has its scientific legitimacy from being published by the academic journal 'International Productivity Monitor', a journal run by the Centre for the Study of Living Standards (CSLS), Ottawa, Canada. This is a scientific center founded by a wide range of donors including the ILO, the OECD, and the Canadian federal government. The EU KLEMS project was founded by the European commission to, in the official websites words, 'create a database on measures of economic growth, productivity, employment creation, capital formation and technological change at the industry level for all European Union member states from 1970 onwards.' (EU KLEMS, 2008). The data gathering project aimed at providing inputs to policy evaluation, especially relating to competitiveness and economic growth and was furthermore intended to facilitate the sustainable production of high-quality statistics by applying the methodologies of national accounts and input-output analysis (2008). During the Summer of 2019, the official website promises an update of the data, suggesting that the project has somehow succeeded in making the data gathering sustainable.

To support this data, other databases are used. Especially data from the World Bank Open Data (World Bank, 2019b) is extracted in the analysis, but also from the International Labor Organization (ILO, 2019). The Danish national statistical bureau, Statistics Denmark (2019), is used mainly to obtain the sparse existing data on Danish offshoring, offshoring referring to the process where a company or institution in a country directly or indirectly hires workers in other countries to perform tasks, often at lower costs than in the offshoring country. It can also be done because skills or machinery is only available in other countries.

2.7.2 Selection of Variables

The variables used are presented in the analysis itself, so this section merely provides an overview of some of the considerations involved in the selection. Having identified the EU KLEMS dataset as the most detailed primary source available, one had to select the variables most relevant to the RQs. That is, to carry out the analysis on a sector level, the author of the thesis had to choose between the variables available in the EU KLEMS dataset. For transparency reasons, these are listed in **APPENDIX 1**. The variables included can generally be divided in 'control-variables' and 'focus-variables'. The control-variables are included to control for the case that changes on the Danish labor market were caused by factors not related to technological change such as demographical changes, economic cyclical changes, and changes in level of offshoring. The focus variables, which relate to

productivity changes and employment levels, support the analysis in approaching an estimation of the degree to which different sectors have been exposed to technological advancements and thus, productivity increases, although productivity increases and job losses can also stem from other factors. For more on the specific variables, see section 4.

2.8 Methodological Reflections

To operationalize the methodological approaches in the paper, it is useful to separate the different parts of the thesis and then discuss the methods used. The methodology of the literature review will not get attention in this section, as this has already discussed in section 2.1 and 2.2.

The analysis uses a combination of methodological approaches. First, the analysis should be understood as a quantitative case study of the Danish labor market and the effects of technological change. The results of the case study are not used to generalize to other countries but merely serve as an example of one case of labor market effects from technological change in a country which is likely to have a relatively high exposure to technological change. The results can thus in further research be used in relation to other countries to discover differences from or similarities with the Danish labor market. Calling the analysis a 'case study' however, would to some scholars be problematic. Robert K. Yin's definition of a case study is often referred to in academic work and it focuses on case studies investigating contemporary phenomena in its real-world context and using data triangulation to address the distinctive technical condition whereby case studies have more variables of interest than data points (Yin, 2014). In this sense, the analysis lacks some features of a case study as it does not use data triangulation. Mostly, the data on Denmark was available only from one source, the EU KLEMS dataset, which made data triangulation on the sector-level impossible. Focusing on the case of Denmark, however, does zoom in on changes in a specific, real-world context and, even though this might be in conflict with some scholars' definition of case studies, it will bear the label 'case study' in this thesis.

Secondly, within the case Denmark, three focus sectors are used making these micro case studies within the case of Denmark. The sectors are compared with each other, and therefore also constitute a comparative analysis of cases with different assumed contexts. David Collier calls this type of comparative analysis a 'contrast of context' comparison, typically used to show how parallel processes are played out in different, context-dependent ways (Collier, 1993).

Using the terminologies of the above scholars and considering that the general aim of the analysis to search for signs of technological change in the Danish labor market, the methodology of the analysis could therefore be operationalized as a case study using contrast-of-context comparative tools to detect theory-based, expected trends.

3 The literature reviewed¹

Although this literature review is divided in four sections, the reader is asked to note that this division is done mainly to present the literature in a meaningful order. The arguments in the literature are categorized in different groups, but this does not mean that they do not overlap significantly from group to group. The first section of the literature review presents arguments from the reviewed literature which explicitly express urgent concerns for the creation of surplus populations and general human joblessness. The second section is also a collection of arguments by different scholars but contrary to the first group, this group does not as such express concerns of human joblessness, but instead of rising inequality as a result of technological change. The third section presents academic work which is more positive than negative about the effect of technological changes on job markets and which empathize the growing need for human workers. The three first sections are internally divided after common topics. Finally, the fourth section warms up for the case study by examining literature relating to technological changes effect specifically on the Danish job market.

To introduce the literature review, I wish to present Mario Pianta's work (2018) which is a literature review noting a series of consensus points in the debate on technological change and labor markets. Pianta proposes a series of 'stylized facts' on the relationship between employment and technology. The most noteworthy of those are that (a) technology is formed by social relations; (b) technological unemployment is a serious issue; (c) the nature of work is changing; (d) different technological strategies have contrasting employment effects; (e) the employment impact of technological change can be observed at the firm, industry and macroeconomic levels; (f) business cycles affect technological changes' employment impact; (g) the impact of technology differs depending on occupations

¹ The literature review in this thesis was originally based on a pilot project carried out by the author on Roskilde University. Some of the literature from this pilot project is also included in thesis which may mean that a few sentences in this thesis' literature review might be similar to sentences in the pilot project literature review. It must however be underscored that the literature review in this thesis is unique and done entirely by the author in Spring 2019. The pilot project can be found in the references (Hoffmeyer & Ma, 2018).

and skill levels; (h) technological advancements foster inequality as corporate profits grow faster than wages (Pianta, 2018, p. 189). He bases these claims on an extensive review of existing literature and data presented in the academic debate and argues that these points are commonly accepted among scholars. However, as we shall see in this literature review, some scholars disagree with some of these arguments, especially, with the last point on inequality.

We now turn our attention to the first three groups of literature; the alarmist, the concerned, and the optimistic.

3.1 Group A: Alarm for Human Joblessness

In this group of arguments, we find literature expressing grave concerns about the developments in technology and the automation of human tasks it brings. Many arguments in this section are centered around the belief that the wave of technological change which is washing in over labor markets these years is fundamentally different from earlier waves. In much of the literature in this category, it is argued that the present wave of technological change might well entail mass unemployment and surplus populations due to the fact that digital and information technologies, computers, and machines with human-like capabilities are technologies with such broad applicability across sectors and countries.

3.1.1 The End of Work and the Marxist Critique

One part of the reviewed literature relating to the problems with this wave of technological change discusses the effects on a theoretical and macro-economic level. A much cited work within this line of argument is Jeremy Rifkin's book 'The End of Work' (1995) which strongly sounds the alarm for a different wave of technological change that could lead to mass unemployment and so-called 'breadlines', i.e. severe economic impacts for certain parts of the population (p. 3). Rifkin uses metaphors such as the new technology wave being a 'new economic disease' to underline his arguments and appeal to feelings of fear. Since then, many

authors have used Rifkin's warnings as a point of departure and from this has grown a Marxist critique connecting capitalism and technological advancements with fears of mass unemployment (Hughes & Southern, 2019; Mason, 2015; Srnicek & Williams, 2015) or societal polarizations (Standing, 2017, 2018). The Marxist argument is based on the concern that certain groups of the population gain ownership of key technologies, skimming the profits of productivity increases while keeping real wages stagnant or falling (Srnicek & Williams, 2015, p. 93). Paul Mason's (2015) starting point is equally the nature of capitalism and technological change and he argues that technological change in the near future will cause a threeway split of the human path; either we follow a path towards stagnating growth and crisis, or we will see radical uprisings and maybe another world war or, instead, we could move beyond capitalism and rescue the world from the first two scenarios. According to Mason, the labor-theory, as presented by Marx, is true when predicting that automation can reduce necessary labor to a minimum so small that human work would become optional (p. 162).

3.1.2 Increasing Inequality

Other arguments for sounding the alarm for human surplus populations authors do not use Marxist theory as a starting point but still focus on the social and economic inequality that they believe technological change and falling labor demand will create. Frederick Pitts, Lorena Lombardozzi & Niel Warner (2017) argue that technological change will mainly cause jobs that are 'meaningful' to humans to disappear and the jobs left for human occupation will be the lowest skilled jobs. Why, they argue, should an employer spend money on new technology when he can more cheaply employ a low-skilled worker, for example by offshoring tasks (p. 152). They also support the worry expressed by Srnicek & Williams that the profits generated from automation-driven productivity increases are likely to be unequally distributed (p. 152). Orlando Gomes (2019) develops an econometric model built on neo-classical assumptions for assessing technological change's effect on society and reaches the conclusion that the new wave of technological change goes hand in hand with inequality because robots can be detached from the workforce while humans cannot. Without regulation, he writes, powerful technology will be on the hands of the few while the many will become increasingly superfluous (Gomes, 2019, p. 96), supporting Pitts et al. and Srnicek & Williams' worries.

Another worried soul, Martin Ford (2015; 2018), argues that automation can create the perfect storm of socio-economic chaos in a lethal combination with climate change and socio-economic inequality. Both Ford and Srnicek & Williams focus on this wave of technological change being different because this wave of technological change introduces technologies which are of such general use that they influence entire economies, reducing the overall demand for human labor (Ford, 2015, p. XVI; Srnicek & Williams, 2015, p. 90). This means that even if new jobs are created, they will require increasingly less labor since the new technologies have such a range of applicability. Srnicek & Williams also points to the speed of technological change being different from earlier technological change waves writing that technological change could potentially soon reach a speed which renders it close to impossible for a large portion of the population to acquire the skills required in new jobs (p. 90).

Who then, according to these authors, will be the first group of people to feel the invisible hand of technological change? The precariat (a label recently reintroduced by Guy Standing), is repeatedly mentioned as an answer to this question in the worried literature group. A low-skilled class with precarious connections to the job market which they fear will become 'an obsolete surplus population' (Srnicek & Williams, 2015, p. 91). Estimates of the percentage of the global labor force belonging to the potential surplus population range between 40 and 74% (p. 92). Srnicek & Williams find that there are not enough jobs worldwide and that a group of people exists who finds themselves outside formal work, relying on minimal or no welfare benefits and informal subsistence work (p. 103). The growing size of surplus populations transfers negotiation power to company owners and makes decreasing job quality and stagnating wages rising concerns, according to Srnicek & Williams (p. 93).

As a solution to the threats of increasing inequality caused by technological change, some of the authors behind the literature in Group A discuss universal basic income (UBI) as a way of meeting the severe challenges posed by technological change. UBI is praised by some and discouraged by others. Pitts et al. (2017) write that UBI could lock the lowest skilled workers in low quality, precarious jobs (pp. 151-152) while Ford (2015, p. 257; 2018, p. 44), Mason (2015, Chapter 10) and Srnicek & Williams (2015, Chapter 6) all agree that the UBI model is one of the answers needed to the challenges of technological change and the future of work.

3.2 Group B: Concerns of Rising Inequality and Changing Skill Compositions but Not Falling Labor Demand

This group of arguments do not call for alarm for human joblessness as such but instead focuses on raising concerns about various kinds of polarizations nurtured by technological advancements: skill polarization, income polarization and political polarization. The arguments categorized in this group share the opinion that we should not worry too much about human joblessness caused by automation and technological advancements as new jobs are bound to come. Joseph Schumpeter's concept of creative destruction is repeatedly referred to in this line of argument. They do however fear that the owners of software and machines will keep most of the generated profits while workers' wages will remain stagnant or even falling in real terms. Unemployment ratios in general, however, are often expected to be kept relatively stable if we manage to reskill workers with the 'right' skills.

3.2.1 The Nature of Work is Changing, The Transition Might Create Rising Inequalities

In the literature placed within this categorization, one word reappears countless times, namely, inequality. Guy Standing is best known for his academic contributions on the precariat class, but the formation of this class seems for him firmly linked to the processes of automation and job-market changes that he observes (2017; 2018), as also argued by authors in Group A. Standing focuses parts of his work on the rapidly growing platform-economies and the very nature of work being under transformation. The terms 'employed', 'unemployed' and 'self-employed', he argues, are increasingly becoming obsolete in a time where people increasingly earn their living through online platforms such as AirBnB, Über, BlaBlacar and TaskRabbit (Standing, 2018, pp. 120-121). Standing suggests that these tendencies will lead to a society where the lowest class, which he calls the precariat, has task-based jobs with no or little union organization or general working condition regulations. Unless societies prepare to handle the new trends, the precariat class could become a population group isolated from the rest of the

population (p. 133). Among the literature in Group B, the precariat, is repeatedly mentioned and a deep worry reigns for this particular group to not be able to adjust rapidly enough to the labor market changes that new technology is causing with great velocity.

The Organisation for Economic Co-operation and Development (the OECD) published a report in 2018 called 'Job Creation and Local Economic Development'. The spirit of the report is optimistic while still containing warnings relating to technological change, especially in some particular countries. OECD countries where the lion's share of new jobs created are in high automation-risk sectors. The results of the report therefore indicate a geographically diverse challenge where 60% of the regions investigated (often regions with the highest educational level and a high percentage of jobs in the service sector) have been able to create most of their new jobs in low automation-risk sectors while regions which already have high unemployment rates and low productivity growth are creating most of their new jobs in high automation-risk sectors (OECD, 2018, p. 19). Geographical differences in job creation are found to be increasing both between countries and within countries (p. 26). Capital and metropolitan regions are highlighted as typically creating more jobs than they lose to automation and doing so primarily in the sectors at low risk of automation. Rural areas, on the other hand, tend to either lose jobs or create jobs in high risk sectors (p. 26). This could indicate that jobless futures could happen in some regions, while other regions nearby experience significant job booms. Finally, the report concludes that a good and wide education system can be a way to counter the negative trends in high risk areas as regions with jobs mainly in the low-automation risk sectors have a higher percentage of people with tertiary education. Additionally, service sector jobs are repeatedly highlighted as being in low risk of automation (p. 26).

Like Standing, the OECD report warns of particular population groups, especially in rural areas, risking exclusion from a rapidly changing labor market. Klaus Schwab (2015) echoes this concern when stressing that in addition to being an economic concern, inequality poses 'the greatest societal concern associated with the Fourth Industrial Revolution' (Schwab, 2015, para. 10). He is convinced the future will have jobs for humans but warns against economic and skill-related stratifications (para. 9). This stratification of society is, according to Richard Freeman who agrees with Schwab's point, the most important thing to fear (2016). Rather than a jobless future, he fears a future in which the wages of workers are stagnant or falling as robots increase their share of high-productivity jobs, while the share of income going to the machine-owners increases, creating an increasingly polarized society (Freeman, 2016, para. 10).

Some scholars focus their work on wage developments. Stephen J. DeCanio uses quantitative data from the US to conclude that the spread of AI and robotization might, indeed as Freeman fears, lead to decreasing real wages, especially in the American manufacturing sector. This, he argues, can happen when the elasticity of substitution between human and robotic labor becomes greater than 1.9 (DeCanio, 2016, p. 280). To DeCanio, this does not seem like an unrealistic scenario and he warns against the proliferation of robotics and AIs causing rising inequality unless the 'returns to robotic assets' are spread equally across the entire population (p. 289). Clemens Lankisch, Klaus Prettner, and Alexia Prskawetz (2019) also focus on wages and use technological change to explain rising wage inequalities. They suggest that governments should make investments in higher education to help to soften the adverse effects of automation processes (Lankisch, Prettner, & Prskawetz, 2019, p. 1). The authors highlight that the skill premium has grown as high skill workers have gained proportionally more wage increases than low skilled workers, who have experienced real wages falling. The declining need for low skilled workers is explained by offshoring, superstar economy, reduction of top marginal tax rates, falling labor union power, declining birth rates, and assortative mating. Finally, they add technological change to the list of explanatory factors (p. 2). The paper introduces econometric models which predict, corresponding to the US reality between 1970 and 2010, that accelerated automation leads to increased GDP per capita and increased skill premium (hence rising wage gap between different skill levels) (p. 6). While DeCanio and Lankisch et al. use empirical data to support their claims, Andrew Berg, Edward F. Buffie, and Luis-Felipe Zanna (2018) build a theoretical model and claim that they have robust results showing that 'automation is good for growth and bad for equality' (Berg, Buffie, & Zanna, 2018, p. 117). The model is based on a neoclassical framework which predicts that real wages decrease in the short run as a result of automation but eventually begin to increase. However, the term "eventually" is connected with a lot of uncertainty as it could last generations (pp. 117-119). The findings of Berg et al. (2018) and DeCanio (2016) do not as such contradict each other as their focus and scientific starting point are rather different but they indicate that wages might respond differently to automation depending on geographical location (as the OECD report focusses on) and industry (as shown by DeCanio).

In David Autor's solo-article from 2015, 'Why Are There Still So Many Jobs? The History and Future of Workplace Automation', he claims that his and many other scholars' research suggest that the problem of automation is not scarcity of work but distribution of work and hence, a political challenge (Autor, 2015, p. 28). His main worry regarding the American society, is that the educational system is not ready to teach workers the skills which will be the most needed in the 21st century because rapid skill polarizations are likely to outrun educational reforms (2015, p. 26). On the point of skill polarizations, Autor is supported by the OECD report (2018) and the work of Maarten Goos, Alan Manning, and Anna Salomons whose research concludes that 16 European countries exhibited wage polarization in different degrees in the period 1993-2010 (Goos, Manning, & Salomons, 2014, p. 2515). Routine-biased technological change and offshoring were according to the authors two important factors explaining this trend (p. 2509). The OECD report builds on this research and reaches the further conclusion that all 23 OECD countries studied experienced a significant decline in middle skilled jobs' share of total employment, indicating large scale skill polarizations in the job market (2018, p. 39). Duncan Gallie, however, raises questions about the universality of these observed skill polarizations (Gallie, 2017, p. 231). He thus explicitly challenges what he calls David Autor's 'task-biased theory of skill development' (p. 227). Gallie presents an interesting review of literature concerned with the structure of skills and skill polarizations in developed economies and concludes that there is

indeed evidence of skill polarizations in some countries but simultaneously there has been produced proof of significant, general upgrading, not polarization, of skill levels in some countries, especially among Nordic countries (p. 238).

Gallie underscores that changes in skill compositions are happening and this does create of threat of societal stratifications - his point is that it happens differently from place to place. A long series of researchers have noted different trends in their work on labor markets in specific geographical areas. Laurie S.M. Reijnders and Gaaitzen J. de Vries (2018) documents a growing share of non-routine jobs in 37 advanced and emerging economies in the period between 1999 and 2007 with Mexico, France, and the UK experiencing the biggest growth in the share of nonroutine jobs (Reijnders & de Vries, 2018, p. 415). The authors in explain these changes partly by technological change and offshoring (p. 412). Daniel B. le Roux (2018) uses the case of South Africa to exemplify how technological change threatens to obsolete the jobs of up to 35% of South African workers corresponding to 4.5 million workers – due to changes in demanded skills (le Roux, 2018, pp. 507-514). Aykut Lenger focuses on manufacturing in Turkey (1985-1998) and the inter-industry effects of technological change (measured as TFP). Lenger finds technological change to increase employment in administrative jobs in the skilled labor-intensive industries while reducing employment in production jobs in the same industries (Lenger, 2016, p. 236). Particularly, he finds that technological change has a negative effect on employment in the unskilled, laborintensive industries in Turkey (p. 246). David Lambert reviews workforce education and technical change bias in the US' agriculture sector and related industries and finds that while low educated workers fell in absolute employment numbers in US agriculture, the amount of highly educated workers (measured per hour worked) increased dramatically (Lambert, 2018, pp. 339–341). Total hours worked in US agriculture fell 77% in the period under study (1947-2010) (p. 338). Carl Frey and Michael Osborne (2013) analyze the employment risks associated with computerization (the process of computers taking over tasks that earlier were occupied by humans) in the US. Their study concludes that 47% of US jobs are in high risk of computerization. Low income jobs appear to be especially at risk (Frey & Osborne, 2017, p. 38). Their model does not, in contradiction to studies of other regions, predict that middle income jobs will be most affected by computerization but rather that low-income jobs will be most exposed (Frey & Osborne, 2017, p. 42). Martin Falk & Federico Biagi conclude that different technologies within ICT has led to an increased demand for workers with a tertiary education in seven European countries (Falk & Biagi, 2017). Sandeep Kumar Kujur uses the manufacturing industry in India as a show case of technological change's effect on employment. He concludes that increasing activity in the industry secured rising employment in the manufacturing industry but that technological change caused a negative dent in that increase (Kujur, 2018, p. 358). Adrian Adermon and Magnus Gustavsson show that Sweden experienced a polarization of wages in the period 1975-2005 (Adermon & Gustavsson, 2015, p. 878). They find that this trend was partly caused by technological change's skill bias during the 1990s and 2000s but not in the 1970s and 1980s (p. 878). Enrique Fernández-Macías argues that there was no general trend of polarizations between 1995 and 2007 in Europe (Fernández-Macías, 2012, p. 157). Instead, he finds a number of different trends in different countries. General upgrading of skills happened in Finland, Luxembourg, Denmark, Sweden, and Ireland while polarization happened in the Netherlands, France, Germany, Belgium, and the UK both measured by educational degree and wages (p. 171). Focusing on automation in Australian container terminals, Victor Gekara and Vi-Xuan Thanh (2018) qualitatively analyze the effect of automation on the local workforce. They conclude that a new type of highly educated, soft skill worker has emerged with capabilities in both computer tasks and tasks requiring soft, human skills (Gekara & Thanh Nguyen, 2018, p. 219). Although automation of tasks in the container terminals has caused falling employment numbers, the authors stress that it is not a simple, unidirectional trend. New jobs emerge as technological change regroups workers and the required skills change towards computer skills and soft skills (p. 230).

The list of academic work on the effects of technological change on different labor markets presented above illustrates how changes are happening across the planet, as Mario Pianta's work also hinted at in the beginning of this literature review, and that one should be careful with universal statements of technological change's effect on labor markets.

3.2.2 Why Large Scale Human Joblessness Will Not Happen

As noted in the section above, many authors are skeptical towards the idea of a jobless future. In this section, some arguments directed at the unlikeliness of human joblessness are presented.

Guy Standing maintains that there does not exist an absolute amount of human work; humans will create their purpose by applying their work-potential in everchanging ways (Standing, 2017, p. 40). Richard Freeman (2016) puts it differently by applying the classic economic concept of comparative advantage. While machines might outperform humans in particular tasks, some tasks will still remain for humans to do since machines will do only what they are comparatively best at doing, he argues. Humans therefore will always find work in the tasks they are the least bad at. This does not however guarantee that the jobs which humans will undertake provide good wages or have good working conditions (2016, para. 8). He bases his arguments on the disruption of the transport industry if the United States and argues that humans will tend to find new jobs when machines begin to outperform humans in specific tasks (Freeman, 2016).

A key argument in Group B is that the spillover effects of technological change creates increased demand for labor in society. One couple of researchers that examine this is David Autor & Anna Salmons (2017) who analyses the correlation between productivity increases and employment in 19 countries using data from EU KLEMS (the same database as I use in the case study of Denmark). They find that technological advances are responsible for some downward pressure on employment but that technological advancements have spillover effects from industry to industry which means that the net effect of new technology between 1970 and 2007 was employment positive – although, it should be noted, this correlation was weakest in latest period under study (2000-2007). This argument is supported by Dev Nathan and Neetu Ahmed's (2018) theoretical paper which notes

that automation creates jobs while at the same time destroying other jobs – in line with the concept of creative destruction.

Another argument for the unlikeliness of human joblessness comes from Martin Upchurch (2018) who discusses the prospects of singularity uses Alan Turing's test of intelligence to argue that the technological breakthroughs needed to reach singularity are still many (Upchurch, 2018, p. 215). Alarms of 'the end of work' and singularity rang in the 1920s, 1930s, 1950s, 1970s, and 1990s but still, Upchurch argues, we are far from robots with *real* intelligence (p. 215). He does not say that singularity and 'end of work' concerns are not important but rather that they are still unripe.

Duncan Gallie's (2017) likewise challenges 'the pessimistic scenario of postwar neo-Marxian theory' (p. 231) by discussing literature on the level of job control (employee's level of freedom when carrying out tasks) and job quality. He concludes that the only major trend is that Scandinavian countries continue to exhibit higher levels of job control for the employed (p. 239). Finally, he argues that technological changes do not seem to increase the level of job insecurity in countries (p. 239). These two features are then used by Gallie to arrive at his final proposal, that although the challenges are many and the solutions few, there is no historical evidence to support the deterministically pessimistic visions of technological advancements' effect on the job market as the outcome will depend upon the choices of policymakers and employers (p. 240).

3.2.3 Policy Recommendations

Many of the mentioned researchers in Group B deals with identifying problems related to technological change but some also deal with possible solutions to these challenges.

Barbara Prainsack and Alena Buyx (2018) aim at providing suggestions to how to mitigate the adverse effects of a rapidly changing job market. An important argument in their paper is that the value of work should not be determined solely by the labor market, but rather according to its importance for society as a whole

(Prainsack & Buyx, 2018, p. 585). They encourage policy makers to prepare for a society with a changing labor market by focusing on health equality, social cohesion, and the flourishing of people and communities, as they write (p. 587). They acknowledge that much uncertainty is connected to predicting the exact transformative processes in the labor market of the 21st century but assume that major changes are coming and that this will put a pressure on equality and health related human thrive. A keyword for handling the challenges ahead of us, according to Prainsack and Buyx, is solidarity (p. 592).

Another solution oriented work is The World Development Report 2019 published by the World Bank (World Bank, 2019a) which highlights how countries, in particular developing countries, must improve tax collection efforts along with investing tax revenues in human development areas such as education and health, in preparation for a future with an increased level of automation. In countries with a relatively low level of investments in human capital, the report estimates that the workforce will become one-third to one-half as productive as it could otherwise be if people lived in good health and received high-quality education (World Bank, 2019a, p. VII). The World Bank report offers three governmental initiatives which could assist the transition towards the labor markets of the future: investments in education, defining a social minimum and strengthening social insurance, and finally, increasing tax revenues, especially by preventing tax avoidance (p. 9). Frey & Osborne (2013) and Lankisch et al. (2019) echo the need for investment and restructuring of educational systems as wages and educational attainment shows a strong negative relationship with the probability of computerization (p. 42). Other recommendations focus on taxing robotic work. In Pengqing Zhang's research (2019) on the skilled-unskilled wage gap, he discusses the option of taxing robotic work. Zhang uses a specific-factor framework to argue that while an acceleration of automation increases the wage gap, a tax on robots will unambiguously decrease this wage gap (2019, p. 500). The paper does not include empirical data but is instead built on a theoretical model.

3.3 Group C: Technological Change Creates Increased Human Labor Demand and Prosperity

This third group of arguments is more optimistic about the relationship between technological advancements and labor markets, arguing that, by and large, technology leads to net positive effects on employment. This literature holds an optimistic spirit when estimating the labor market effects of the new wave of technological change and generally, concerns about technological change leading to increased levels of inequality are not expressed.

3.3.1 Why Robots Create Jobs

James Manyika et al. (2017) writes on behalf of the McKinsey & Company Institute which issued this report which has the main argument that people will continue to work, together with machines, and those workers who are substituted by machines will generally find other employment as the demand for human labor will increase (Manyika et al., 2017). Regarding the question whether this wave of technological changes is fundamentally different from earlier waves, Manyika et al. argue that the anticipated shift in activities of the labor force is of 'a similar order of magnitude' as previous shifts, for example in agriculture and manufacturing in the United States. Both of these shifts were accompanied by the creation of new, unpredicted jobs (p. vi). They expect employment growth and productivity growth to be positive in the coming 50 years (p. vii).

Erik Brynjolfsson & Andrew McAfee (2011) elaborate on the to the idea of humans working closely together with machines – called 'cobots' when referring to this relationship. They use the case of the US and present three explanations to why job creation has been staying low in recent decades (Brynjolfsson & McAfee, 2011, pp. 12–15): According to the cyclical explanation, demand is just too low at the moment, meaning that when general demand increases, jobs will be created. The stagnation explanation argues that since 1970, the US have been stuck on a technological plateau where the low hanging productivity fruits have already been picked. We are, in the stagnation-explanation, waiting for a new industrial revolution and as a result of this stagnation, US relative power over fast growing BRICS (Brazil, Russia, India, China, South Africa) is shrinking. Finally, they describe the end-of-work explanation; the US is in fact experiencing a technological explosion where automation destroys jobs. Brynjolfsson & McAfee write that they identify most strongly with the last group (which indicates that they do not belong in this group), but they have some important reservations (which justify their spot in Group C). They highlight that some human skills are becoming more valuable than ever while other skills are becoming increasingly worthless. These people with 'worthless' skills, they argue, are losing the race against the machine (pp. 15-16). In the other end of the spectrum, creative entrepreneurs are the ones who will benefit from skills that allow them to work closely together with machines. The authors believe that the increasing number of available, mid-skilled workers in a combination with cheaper technology is positive for new job creation (p. 55). Brynjolfsson & McAfee do not subscribe to the fear that technological change will lead to increasing inequality because technology will make it possible for ever more people to start companies both nationally and globally and an increasing population group will be able to acquire 'superstar' compensation. Although winner-take-all mechanics have the potential to lead to disproportionate rewards to the top performer in each industry, they write, the important feature to focus on is that there is no maximum of markets that can be created. In theory, they argue, millions of people could be a global leader millions of different value-creating industries (p. 58). This optimistic attitude towards the coming developments in technology is shared by Ben Vermeulen, Jan Kesselhut, Andreas Pyka, and Pier Paolo Saviotti (2018) who use an evolutionary economic model of multisectoral structural change along with labor economic theory and expert predictions, to develop an estimate which states that the job losses experienced due to automation in 'applying' sectors is counterbalanced by the creation of jobs in 'making' sectors as well as in 'complementary and quaternary, spillover sectors' (Vermeulen, Kesselhut, Pyka, & Saviotti, 2018, p. 1), a point also made in a European context by Gregory, Salomons, & Zierahn (2016). According to these authors, we, as a world society, are facing the usual structural changes and not the end of work (p. 1). Their policy suggestions include measures of robot-taxing and an emphasis on encouraging entrepreneurship, education, and upskilling.

Ross Boyd & Robert Holton (2018) also discuss whether robotics and AI poses 'unprecedented' challenges to society and are less unidirectional in their conclusions. They claim that this wave is both distinct from and similar to previous waves of technological changes (Boyd & Holton, 2018, p. 343). Technological determinism is discouraged in their paper, as in Duncan Gallie's work, and instead they wish to open the door to an understanding of the future as neither dystopic, nor utopic but rather changeable and manageable (p. 343).

Finally, Mariacristina Piva and Marco Vivarelli (2018) provides (a) a theoretical discussion of technological change's effect on employment and (b) an analysis based on empirical data from the period 1998 to 2011 for 11 European countries (Piva & Vivarelli, 2018, p. 13). They also find a positive relationship between technological change and employment by using the proxy-indicator R&D-expenditures revealing that the number of employees in a given sector is net positively correlated to R&D-expenditure, mainly due to the medium and high-tech sectors (p. 13).

3.3.2 Policy Recommendations

Although many optimistic attitudes are displayed in this group of arguments, it is underscored that many hurdles must still be overcome in order for the positive effects of technological change to come true.

Manyika et al. (2017) highlight that policy-makers must create innovating policies facilitating the transitioning labor markets. This, the McKinsey-report suggests, could be done through a restructuring of education, income support, and social safety nets (Manyika et al., 2017, p. vi). Brynjolfsson & McAfee (2011) brings forth a full list of 16 elements that American policy-makers should consider as a response to a changing job-market. A key policy advice among these, is to invest in education (p. 62). Secondly, they highlight encouragement of entrepreneurship (p. 63).

Thirdly, communication and transportation infrastructure is regarded as an essential step to increase productivity (p. 63).

3.3.3 Supportive Arguments to Group C

This sub-grouping of arguments does not as such discuss whether technological change will lead to mass unemployment or not but have been placed in this section because their research could potentially be used to support the arguments in Group C.

Paul K. McClure's research (2018) investigates fear of technological change including robots, AI, and other complex technologies in the US. He finds that a group of technophobes exist in the US and that the size of this group is 37%, based on interviews with 1.541 respondents. Individuals from this group report significant fear of technological change and additionally are likelier to report mental illnesses (McClure, 2018, p. 139). Approximately 28% of all respondents report that they are afraid or very afraid of robots replacing human labor. Technophobes are, according to McClure's research, more likely to be female and have less than a college degree. His findings also suggest that technophobia is highly related to general anxiety. This work could be used by scholars to argue that an irrational fear of technological change exists in a significant part of the population and that the positive labor market effects of technological change being suppressed by this fear.

Another scientist refraining from discussing mass unemployment and automation is Timothy F. Slaper (2019) who instead uses the case of Indiana, US to research the employment losses in the sector of durable goods manufacturing (Slaper, 2019). The results of the quantitative analysis of this case indicate that offshoring – not technological change – was the main driver of employment losses in the sector in the period 2001-2016 (p. 34). Technological change and offshoring could not explain all job losses, other factors where hence at play too. Slaper's work could potentially be used to counter some of the shaming which automation, robots, and other technological change is receiving in the public debate relating to job losses.
3.4 Literature Relating to Technological Change's Effect on the Danish Labor Market

This section presents literature dealing with technological change's effect on the Danish labor market. Emphasis is on the work of McKinsey & Company (2017) and Andersen et al. (2017) which are very much too versions of the same work; one is in English and one is in Danish. The English version (Andersen et al. 2017) was published eight months before the Danish version (McKinsey & Company 2017). It is worth noting that while no authors are registered on the Danish version made for the Danish government, the English version was done by The Tuborg Research Centre For Globalisation and Firms and McKinsey & Company and has the following authors accredited: Jens Riis Andersen, Bjarne Corydon, Jacob Staun, Jacques Bughin, Johannes Lüneborg, and Philipp Schröder. Most noteworthy on this list is maybe Bjarne Corydon, a prominent Danish ex-politician for the Social Democrats. The reports are neither peer-reviewed nor published in an academic journal.

Now to the contents of the reports. References are made to both versions when possible, but emphasis is put on the Danish version. The report made for the Disruption council of the Danish government, estimates that around 40% of worked hours in Denmark can be automated with existing technology (Andersen et al., 2017, p. 19; McKinsey & Company, 2017, p. 1). Their studies of 50 years of data from Statistics Denmark, EU KLEMS, and the OECD indicates that the average work week in Denmark has been shortened by nine hours as a result of the doubling of the productivity (McKinsey & Company, 2017, p. 2). The report is based on three scenarios with varying speed of technological adaptation. In the midway scenario, the authors estimate that the shift in the job market will not be significantly more industries than has previously been affected by technological change (p. 2). In the manufacturing sector, the report highlights that reshoring (aka. backshoring) can be a way for technological change to keep industries in Denmark which would otherwise have been offshored to countries with lower wages. Regarding the

changes in the skills needed, the report suggests a special focus for workers on skills related to social understanding, creativity, problem solving, and advanced digital and analytical skills (p. 3). The three task types with the highest potential for automation in Denmark are said to be information extraction, data analysis, and predictable physical labor (p. 4).

The direct, downward pressure on employment from a 1% productivity increase are estimated to be 0.2-0.3% but historically, the report highlights, the demand spillover effects of productivity increases and the creation of new types of jobs has more than offset this downward pressure and secured stable overall employment levels (p. 5). These estimates are done with the model prescription of David Autor & Anna Salomons (2017). The report warns – contrary to the end of work theory – that Denmark could lack 20.000-45.000 highly skilled workers in 2030 due to the changing skill composition of the job market (p. 10) and the expected increase in demand. Paradoxically however, the report also estimates that 10-15% of the workforce (250-300.000) risk being trapped by automation because they are in highly automatable jobs and when changing job, they tend to move to jobs with the same level of automatability (p. 11). This group of people typically works in operation and transport or physical labor jobs (p. 12).

Three other sources also use Denmark as a starting point in their research on technological change's effect on labor markets and societies. Ana Abeliansky and Klaus Prettner (2017) find a negative correlation between the growth rate of robot density and the growth rate of the population. Their model predicts a 2% reduction in the growth rate of robot density for every 1% increase in population growth (Abeliansky & Prettner, 2017, p. 1). Robot density is measured as robots per 10,000 employees in manufacturing (p. 9). The authors conclude that countries with significant demographic challenges, often in the form of falling population numbers or an ageing population, will be pioneers in adopting and/or inventing new automation technologies (p. 18). Jan Stentoft Arlbjørn and Ole Stegmann Mikkelsen (2014) is a journal note which argues that automation should be used to maintain production jobs in Denmark through so-called backshoring (Arlbjørn &

Mikkelsen, 2014, p. 60) thus supporting the McKinsey reports' emphasis on backshoring. The note is based on a survey conducted with 843 manufacturing companies in Denmark. The Organization of Engineers Denmark, IDA (2018) uses panel data from 565 member-companies to estimate the potential gains from increasing the level of automation in Danish companies. They point to a lack of engineers, IT-specialists as well as other types of high skilled professions as the biggest barrier for implementing automation (IDA, 2018, p. 2). Many respondents in the survey report that automation has 'saved' jobs from being offshored (p. 2) echoing Arlbjørn & Mikkelsen and the McKinsey reports. The report concludes that an automation potential of 66 billion DKK exists in Denmark, i.e. a profit of that amount could be obtained if further automation using existing technology was implemented (p. 2).

3.5 Minding the Gap

The above literature review has shed light on the debate on technological change's effect on labor markets all over the world, including Denmark which will be the focus country of the analysis following this chapter. The gap in the debate which thesis fills, is one within the analysis of labor market trends in Denmark over the past four decades. The literature coming closest to doing this are the McKinsey reports (Andersen et al., 2017; McKinsey & Company, 2017). However, the reports focus more on providing a status-quo description in combination with near-future estimates of the effects of technological change the Danish labor market and less on a retrospective investigation. Only when it comes to trends within GDP and weekly worked hours do the reports analyze recent past trends in depth. The reports, like the IDA report (IDA, 2018), repeatedly return to dealing with the present potential benefits of an increased level of automation on Danish workplaces.

The analysis will thus be unique and value adding when it analyzes trends within a series of labor market variables between 1975 and 2015, providing insight into how different sectors with different assumed exposure to technological change have developed in significantly distinct ways during these eventful decades.

4 Analysis – The Case of Denmark

The aim of this analytical chapter is to gain insights into trends in the Danish labor market which can have been affected by technological change. A key variable of interest is employment because this is the variable is so commonly referred to in the debate on technological change; will employment numbers fall or increase? Some Danish industries and sectors have since 1975 experienced dramatic job losses and the analysis thus investigates which other changes these job losses have been accompanied by and why other sectors have seen contrary trends.

The structure of the analysis is as follows: The first section 'The Case of Denmark – Introduction' provides basic insight into the Danish economy to give us an overview of which type of economy we are focusing on. The first figure in the introduction serves for controlling for changes in variables such as of working age population (as proxy variable for work supply) and the general shape of the economy (measured with GDP, as proxy for general demand conditions). Controlling for these variables adds legitimacy to the analysis' later discussion of the reasons for job losses because it thus becomes easier to detect the role played by technological change in the observed trends. After this overview of the Danish economy and employment trends in Danish sectors, a three focus sectors are chosen as representatives of respectively high and low exposure to technological change and the automation processes it brings. These sectors are then analyzed in more detailed and compared to see how trends in the sectors differ and thereby what stands out in high-exposure sectors/industries.

4.1 The Case of Denmark – Introduction

What do we know about Denmark as an economy which might affect one's expectations about technological change's effect on the Danish labor market?

The Danish economy is characterized by having a relatively high GDP/capita like many of its Western European neighbor economies (World Bank, 2019). In **FIGURE** 2, we see how Danish GDP has grown faster than the population, and hence

increased the GDP/capita significantly since 1975. From the same figure, we can also conclude that the Danish working population has been slowly growing along with total employment, measured as persons engaged. When measuring employment, the EU KLEMS dataset distinguishes between persons employed and persons engaged. The latter includes self-employed people while the first excludes these. The variable 'persons engaged' is therefore more relevant to an analysis with a focus on automatization processes where employment-type has little relevance.

As the linear trendlines' equations tell us in **FIGURE 2**, employment numbers has risen faster than population numbers and consequently it is logical that, as **FIGURE 3** also shows, the unemployment-ratio have fallen.



FIGURE 2 – DENMARK, OVERVIEW, 1975-2015

Sources: Data extracted from *Jäger (2018); **World Bank (2019b); ***ILOSTAT (2019) and processed by the author. Dotted lines: right vertical axis.





Source: Data extracted from World Bank (2019b) (population data) and ILOSTAT (2019) (unemployment data) and processed by the author.

At this point, I shall explain why the different variables used in the above figures were chosen. The variables used in the figures above are used to control for other non-technology-related reasons for sector-specific employment declines. The GDP-data was extracted from the World Bank Open Data (World Bank, 2019b) and used to determine whether demand in general in Danish society was decreasing or increasing in the period. Other variables could have used to determine this, but GDP as a macro-level indicator of the general shape of the economy can be used to support the argument that it is unlikely that employment fell in the focus sectors due to a sloppy economy and falling general demand. As this argument works logically, it was chosen to keep the analysis as simple as possible. Note that the GDP of specific sectors is indeed described by the gross value added-variable which we shall later use. However, this sector-specific GDP does not do the job of saying anything about the general shape of the economy or general demand.

The working-age population data was equally extracted from the World Bank Open Data to control for the case that labor supply was causing employment changes in the focus sectors. Ideally, it should also be controlled whether the supply of labor had the right skill level, but no simple indicator for this could easily be incorporated in the analysis, as the EU KLEMS data did not include data on skill levels and other sources were sparse in their data on this. Therefore, the working-age population variable was used as a 'best available' method to control for labor supply. Finally, variables relating to employment are not so-called control-variables, but rather focus variables included to later discuss the general risk of mass unemployment caused by technological change.

Having seen what the Danish economy looks like at first glance, we need to dig deeper into what work people in Denmark are engaged with. A relatively high GDP per capita (World Bank, 2019b) makes Denmark likely to have a high proportion of its jobs in the service sector as many countries historically has gone through this trend (World Bank, 2019b). Indeed, when observing 10-year interval averages of employment numbers within the main sectors in **FIGURE 4**, we can see that this holds true also in the case of Denmark. Employment numbers in the 40-year period were always biggest in the 'Community Social & Personal Services' sector (henceforth, social services) which is mainly a service sector. Within this sector are the sub-industries 'Public Administration and Defense; Compulsory Social Security', 'Education', and 'Health and Social Work'.



FIGURE 4 – DECENNIAL AVERAGE EMPLOYMENT IN DENMARK, ALL SECTORS, 1975-2015

Source: Data extracted from Jäger (2018) and processed by the author. Employment numbers for 'Mining and Quarrying' are too small to be seen on the chart. Total employment within this sector ranges from 3.000 person engaged in 1975 over 6.000 in 2012, landing on 4.000 in 2015.

A short note on the selection of including this sectoral employment: with regards to the variable intended to exhibit trends of employment changes in specific sectors, data in many different databases were abundant; this is a carefully observed variable. Two variables relating to employment are offered by the EU KLEMS dataset; persons engaged and persons employed. Since the analysis needed to know how many people were working to add value in the different sectors, it was somewhat irrelevant whether these persons were self-employed or under employment of someone. The variable 'persons engaged', where everyone is included, was therefore judged as the most suited variable of the two.

Now back to the results of **FIGURE 4**. Social services' dominance with regards to Danish employment in the period only grew stronger with the years as its share of total employment grew from 27% in 1975 to 37% in 2015 (as can also be sensed by comparing the orange bars in **FIGURE 4** with the blue bars). The second largest sector was 'Total Manufacturing' (henceforth, manufacturing) in the period 1975-1985 but had become the third largest sector by the decade 1996-2005, overrun by 'Wholesale & Retail'. The intense struggle for the spot as the fourth largest sector, 'Professional, Scientific, Technical, Administrative and Support Service Activities', leaving behind the fifth place for 'Construction'. Most dramatically, 'Agriculture, Forestry & Fishing' (henceforth, agriculture) saw an employment drop from a fourth place in 1975-1985 to an eleventh place (of fourteen) in 2006-2015.

The two most imploding sectors when it comes to employment numbers in Denmark was thus manufacturing and agriculture. The EU KLEMS data reveals that these two sectors combined saw a fall of 344.000 in total employment numbers between 1975 and 2015. In relative terms, the sectors accounted for 28% of total Danish employment in 1975 but only 12% in 2015. It is therefore fair to conclude that we are here looking at fundamental changes in the Danish labor market composition, playing out over just a 40-year period.

Notably, the two implosions seem to have opposite acceleration features; while agriculture's employment losses seem to have been slowing down recently, job losses in manufacturing seem to be accelerating. If technological change has indeed played a significant role in causing these trends, this difference could well indicate

that new technologies affected agriculture first and only later managed to adapt to the manufacturing processes.

Moving on with the analysis. When looking at employment from a technologicalchange perspective, it is crucial to control for hours worked since decreasing employment numbers could happen at the same time as increasing hours worked per person engaged meaning that employment numbers would be dropping partly because workers took upon them more and more hours per week.

FIGURE 5 controls for this by showing which sectors had averagely more and which had less working hours registered relative to the number of hours registered in 1975.



FIGURE 5 – AVERAGE YEARLY TOTAL HOURS WORKED RELATIVE, 1975 = 0, 1975-2015, ALL SECTORS

Source: Data extracted from Jäger (2018) and processed by the author. Employment numbers based on persons engaged.

Several trends can be concluded from the figure above, but one is clearer than the rest; service sectors generally increased the number of hours worked while manufacturing, construction and agriculture lost significant shares of hours worked. This corresponds well with the declining employment numbers in these sectors but in addition to employment data, data on total hours worked controls for the case that workers were laid off because their colleagues took upon them more hours which would produce falling employment, but stable or increasing number of hours worked.

Another noteworthy feature of **FIGURE 5** is that, on average, each year has seen a 14.752 hour decline since 1975 in the Danish labor market's hours worked as a whole. Seen together with **FIGURE 2**, which showed increasing total employment numbers, this tells us that the average number of hours worked per person engaged in Denmark has fallen in the period which corresponds well with other literature on the topic. The hour-results from agriculture and manufacturing refute the case that employment has gone down because hours worked has gone up. Indeed, the plummeting hours put into these sectors tell the story of sectors with less need for human labor. It will then be interesting to see later in this analysis if the trends in value added and output within these two sectors are falling too.

This introductory chapter on the Danish economy between 1975 and 2015 has exhibited a country with stable growth in GDP and a falling unemployment/working population ratio. In general, more people work now in Denmark compared to the 1970s and 1980s but combined, they now work slightly fewer hours than back then. Different sectors, however, have had very different experiences in this period. While many service sectors have seen booming employment numbers along with a growing number of total hours worked, other sectors, especially manufacturing and agriculture, has seen plummeting numbers for total employment and hours worked. This brings us to the next section, which has the goal of selecting a number of focus-sectors by identifying sectors with assumed differences in their level of exposure to technological change in order for the analysis to provide insight into sector-specific trends between 1975 and 2015.

4.1.1 Selection of focus sectors

Having presented some basic features of the Danish labor market and the trends of change experienced since the 1970s, we again turn our attention towards technological change's share of responsibility for the changes seen within the Danish labor market. Using estimates from Andersen et al. (2017), we can determine which sectors in Denmark are likely to have been the most exposed to technological change in recent decades and likewise, which have been the least exposed. This information will be used to select focus sectors which are then analyzed in depth to understand the differences in trends.

As mentioned in the literature review, the McKinsey & Company report (2017, p. 4) concludes that the job tasks most exposed to automation are information extraction, data analysis, and predictable physical labor. The least automatable tasks are according to the report's estimates leadership and development of personal, application of expertise, and interaction with humans (p. 4). To be able to translate these tasks to sectors, we need to get some job titles connected with these tasks. Examples of these are found on the report's page 8. From these estimates, it seems clear that operators and transport workers, builders, and service workers are among the most exposed to automation while specialists, leaders, and caretakers and teachers are the least exposed. As these job titles are contained in many different sectors, we are not yet ready to point to specific sectors being most or least exposed to technological change.

Much of the literature in the literature review of this thesis researches how technological change affects the manufacturing sector (Abeliansky & Prettner, 2017; Arlbjørn & Mikkelsen, 2014; DeCanio, 2016; Kujur, 2018; Lenger, 2016; Slaper, 2019) and manufacturing could therefore be a good candidate for representative of a high exposure sector. It is also a sector which lives up to requirements of having a predictable physical labor, as noted by McKinsey &

Company (2017). In the EU KLEMS dataset, the sector called 'Total Manufacturing' is comprised of 11 sub-industries. Considering the above reasoning, manufacturing was chosen as a representative of a sector with high exposure to technological. The agricultural sector was also considered and **APPENDIX 2** shows that the analytical results would have been the same to a large extent, had this sector been chosen instead of manufacturing. However, we keep the sector of agriculture in the peripheral focus of the thesis and we shall use data from this sector again in section 4.2.2, assuming it is indeed a high-exposure sector.

The manufacturing sector was the second largest sector in Denmark throughout the period 1975-2015 measured as value added with current prices² falling short only to the social services sector. In this time period, the sub-industry 'Chemicals and chemical products' became by far the most value-adding industry within Danish manufacturing, producing 27% of the value added in manufacturing by 2015 (Jäger, 2018). The sub-industry 'Machinery and equipment n.e.c.' was also an important part of Danish manufacturing throughout the period, responsible for 15% of the value added in manufacturing by 2015 (2018). It is not difficult to imagine that these sub-industries depend quite heavily on technology, as production in both cases generally happens in relatively predictable and monotonous environments with relatively little human interaction needed – a habitat which many robots and software-coordinated systems are comfortable working in according to, among the McKinsey reports (2017; 2017). The assumption that other sources, manufacturing is highly dependent on technological change is thus supported by the literature reviewed.

To select the low-exposure sector, one could ask what the opposite sector of manufacturing is. Put differently, which sector would have a high level of interaction with humans, application of expertise, and varying and situation-dependent skills needed? When looking through the EU KLEMS dataset, the entrance called 'Community Social and Personal Services' (called social services

² While variables using current prices have generally been omitted in the analysis due to the need for time-dependent comparisons, we here use it only to get single-year, relative impressions of the size of the different sectors.

in this thesis) seems indeed appropriate. Being the biggest sector throughout the period in Denmark measured as value added with current prices, it is comprised of only three sub-industries, namely 'Public administration and defense; compulsory social security', 'Education', and 'Health and social work'. Within these industries it is inherently problematic for existing computers and machinery to substitute humans because high levels of social skills are needed for many of this sector's tasks. Social services is thus a sector where one can assume that the exposure to technological change is significantly lower than in manufacturing.

To strengthen the argument of the analysis, another sector assumed to be somewhat similar to social services when it comes to the level of technological exposure, is identified: 'Accommodation and Food Service Activities' (henceforth, accommodation). Having no sub-sectors, accommodation is also one of the smaller sectors in Denmark measured as value added in current prices. Accommodation comprised only 1.6% of total value added in Denmark in current prices in 2015 (Jäger, 2018) but lack of size should not necessarily disqualify in this selection process. For the diversity of the analysis, it is convenient to have both a small (accommodation) and a big sector (social services) included. As a sector with a high level of customer contact (accommodation) and fine-motoric skills (food services), it is also a sector where new technology does not yet surpass human capabilities.

See more about the selection process of these industries in the designated methodology section, **SELECTION OF FOCUS SECTORS**. Before us, we therefore have a sector specific comparative case study analysis of three sectors: manufacturing, social services, and accommodation.

4.2 The Case of Denmark – Sector Specific Comparative Case Studies

Before digging into the data, a few notes on this comparative case study should be made. When exploring why jobs have disappeared in a sector, it becomes central to understand the nature of the specific sector in order to give a qualified estimate of whether technological change is to blame for the jobs lost. In a country's national accounts of employment in a sector, a relative decline in employment can be the result of a wide range of changes. Among these, some important factors are displayed in **FIGURE 6**.



FIGURE 6 – SOME DOWNWARD FORCES ON EMPLOYMENT

In this analysis, it is important to control for as many of the above variables as possible in order to more accurately determine the role played by technological change. This has been possible in only some cases. The managerial productivity increases could not be controlled for since there was no direct or indirect data on it in any of the datasets used. Furthermore, the introductory section on Denmark in this analysis, provided data on the size of the working age population which is the closest this thesis will get to controlling for insufficient supply of labor. A more thorough analysis would include variables on the most common skill levels required

to be in the case sectors and then observe the size of this population instead of the whole working age population. This, however, is beyond the detail level of this thesis. This is also true for the variables controlling for decreasing demand. Here, this analysis uses GDP where a more optimal measure would be the specific demand for the most common products or services of the case sectors.

The case for technological change being the primary driver of job losses is best in a scenario where there is a sufficient supply of labor, stable or decreasing hours worked per person engaged, stable or increasing demand for the sector's goods/services, increasing productivity, and low levels of offshoring in the sector. It therefore makes sense to zoom in on the data, focusing on specific sectors where qualified estimates relating to technological change's share of the blame can be made by testing for the variables mentioned above. This is done in the following sections which review selected key variables on the chosen case sectors, all in the name of searching for the effects of technological change on the Danish labor market.

To control for as many of the factors in **FIGURE 6** as possible, six useful variables were identified within the EU KLEMS dataset. The selection process of these variables follow here:

When choosing the variable for output, the EU KLEMS offers a number of options. There is a variable called 'Gross value added at current basic prices (in millions of national currency)', one called 'Gross Output at current basic prices (in millions of national currency)', another one is 'Gross output, price indices, 2010 = 100' and finally some related variables calculated in a technically different way, but measuring the same (Jäger, 2018, p. 6). All of these variables measure the output of sectors and industries using different approaches. The chosen two variables controlling for disappearing sectors became 1) 'Gross value added, price indices, 2010 = 100' which measures the value added in the sector and converts it to relative prices with the year 2010 defining the 100-level, thus controlling for inflation and 2) 'Gross output, price indices, 2010 = 100' which does almost the same, except it does not subtract production costs from the total output thus measuring only the

stream of money through the sector. Value added is the difference between a company's sales and its purchases of goods and services from other companies (Samuelson & Nordhaus, 2010, p. 390). When talking about the value added, there can be distinguished between gross value added and net value added, where gross value added is the value added before intermediate inputs (non-finished products) are subtracted (U.S. Bureau of Economic Analysis, 2018). The analysis uses gross value added as a measure of how much value workers accomplish to add. When simultaneously keeping an eye on total hours worked and number of people engaged, one can use gross value added to detect productivity changes and sector/industry activity level (for example an industry's falling or rising importance on the Danish labor market). This allows us to understand whether a given sector is actually doing anything valuable to the market and if the sector is doing so increasingly or decreasingly, as years can be compared when using this variable. The addition of the output variable, 'Gross output', gives us insight into the volume of the money stream flowing through the different sectors, not the value added during this process. Together, these variables make us capable of understanding how the importance of the sectors has changed over time.

The variable for hours worked per week was calculated by dividing the total amount of yearly worked hours of all persons engaged with the number of persons engaged each year. To include a 5-week vacation period per year, this number was then divided by 47 (52 weeks minus 5 weeks). Therefore, the data on hours worked per week cannot be compared with other data as it is not certain that the same methodology has been applied. In general, the hours worked per week seem low, but the point of including this variable was solely to determine whether the persons engaged worked more or less in the period. The absolute numbers were therefore irrelevant, whereas the differences between the numbers of different years were of interest.

Finally, variables that measure productivity changes were needed in the analysis' attempt at detecting technological change's effect on the sectors. Two variables were used here; Gross value added per hour, volume indices, relative to 2010 and

TFP growth (based on value added per hour), also relative to 2010. The TFP data in EU KLEMS only cover the period 1996-2015, while the value added per hour worked variable goes back to 1975 as the rest of the variables. Choosing the first variable, value added per hour, was done with the purpose of finding a variable that could give a rough picture of productivity changes. The EU KLEMS only provides the chosen variable for this purpose. The TFP variable however, has both brother and sister variables in the EU KLEMS dataset: 'TFP (value added based) growth, $2010 = 100^{\circ}$, 'TFP (value added per person employed based) growth, $2010=100^{\circ}$, and 'Contribution of TFP to value added per hour worked growth (percentage points)'. The differences between these related variables quickly becomes rather technical. The chosen variable was based on value added per hour, which was another variable in the analysis. This was one reason for choosing it, giving a sense of continuity in the analysis. Another reason was that the TFP-variable based on value added per hour worked did the job of measuring the TFP growth of each sector in a simpler way than some of the other TFP variables which focused on the 'contribution of TFP to...'. Lastly, it was important that the TFP variable was not based on 'persons employed' as the thesis systematically avoids this measurement method in favor of 'persons engaged'. Thus, all needed variables were chosen.

For any further clarifications on the EU KLEMS variables, the reader is invited to study the methodological details in the paper published by Kirsten Jäger (2018) along with the data.

4.2.1 Comparing Manufacturing with Social Services and Accommodation

The first variable we shall include is simple sector-specific employment numbers, measured as the number of persons engaged within a sector (differently from persons employed which excludes self-employed). This variable is a so-called 'focus variable' for the analysis, different from the control-variables, because it is suspected that technological change has a direct effect on employment numbers. Below, data from 1975 to 2015 is presented.



FIGURE 7 - EMPLOYMENT IN MANUFACTURING, SOCIAL SERVICES AND ACCOMMODATION

Source: Data extracted from Jäger (2018) and processed by the author.

As can be seen in **FIGURE 7** employment rose steadily in social services and, a bit slower, in accommodation while falling in the case of manufacturing. However, we will not yet conclude that technological change destroyed employment in manufacturing while it left the two low-exposure sectors alone. We need to control for more of the variables mentioned in the previous section.

We therefore move on to compare the hours worked, a control-variable in this thesis, to control for the case that employment fell in manufacturing because fewer people took upon them more hours. In **FIGURE 8** below, we can see that the number of hours worked per week per person engaged has generally been falling ever so slightly in all three sectors in the period under study. A small difference between the sectors is that from 1994 and onwards, manufacturing and social services began an ever-so slight increase in the number of hours worked per week while accommodation continued to decline.





Source: Data extracted from Jäger (2018) and processed by the author. 47-week work year assumed.

Nevertheless, we can rule out the concern that fewer people took upon them more hours causing the employment declines experienced in the manufacturing sector.

The next task of the analysis is to check whether the sectors under study grew in importance during the period. This is done with the two control-variables 'Gross value added' and 'Gross output'. This is important since a disappearing sector measured by value added or output might be simply disappearing from the country rather than experiencing automation and technological change destroying jobs. Falling employment numbers alone do not mean that a sector is disappearing but falling employment numbers combined with falling value added and output numbers is a strong indication that the sector is indeed evaporating into thin air or, less figuratively put, moving out of the country.



FIGURE 9 – VALUE ADDED IN MANUFACTURING, SOCIAL SERVICES AND ACCOMMODATION

Source: Data extracted from Jäger (2018) and processed by the author.

FIGURE 9 shows the data on gross value added relative to 2010. From the chart, we can quickly refute the case that any of the sectors under study are vanishing as they are in fact steadily increasing their gross value added. For manufacturing, this growth seems to be both slightly slower and have slowed somewhat down in recent decades, but the growth remains positive for the time being. Below, in **FIGURE 10** we see that the output-variable, controlling for the same as the value added variable, tells very much the same story, namely one of steady growth in all three sectors.



FIGURE 10 - OUTPUT IN MANUFACTURING, SOCIAL SERVICES AND ACCOMMODATION

Source: Data extracted from Jäger (2018) and processed by the author.

A growing gross output is an indicator that the sectors increase both their input of material and capital and their output of products and services. We have now seen that the high-exposure manufacturing sector has seen falling employment and falling hours worked but maintained growth in value added and output.

In the rest of this comparative analysis, we focus on variables relating to productivity. These are focus-variables in the analysis as they directly relate to technological change; new technology tends to increase productivity over time. The first productivity variable we shall include is gross value added *per hour worked*. Gross value added per hour worked is a variable which tells us how much each worker adds value to the economic actor each hour. In **FIGURE 11** we see that this variable has been growing rather slowly for social services and accommodation while growing notably faster in manufacturing.

FIGURE 11 – VALUE ADDED/HOUR IN MANUFACTURING, SOCIAL SERVICES AND ACCOMMODATION



Source: Data extracted from Jäger (2018) and processed by the author.

The trends in **FIGURE 11** indicate that, one way or another, manufacturing companies have managed to increase the amount of value added in average per hour worked faster than social services. The sector of accommodation, on the other hand, has seen plummeting numbers for value added per hour worked since the beginning of the 1990s. However, we conclude that this difference or any other difference is certainly due to technological change. We might, nevertheless, be able to find trends which support the likelihood of technological change being an important factor in explaining these trend differences.

The final variable we will include is the total factor productivity growth (TFP) which is a variable used in econometrics to measure non-capital, non-labor related productivity increases (Autor & Salomons, 2017; Comin, 2006). TFP is a neoclassical accountancy tool originally used by Robert Solow (1956) that assumes perfect market competition and accurate growth rates of inputs and in return offers a measure of non-labor and non-capital related contributions to productivity growth (Comin, 2006). With care, TFP can be used as an indicator of innovation

development as it minimizes the role of fluctuations in wages and the stock market. Differences across countries in TFP is therefore to a certain degree linked to differences in either the technology applied by countries or the efficiency with which technologies are applied (p. 2). In neoclassical economics, long-run growth in income per capita must ultimately be driven by growth in TFP (p. 1). TFP cannot be claimed to measure the level of technological change, but it provides a variable which is highly sensitive to the effects of technology on productivity. It is thus used to 'clean' productivity increases from other factors, leaving behind a measure for how efficiently and intensely inputs are utilized in production (Comin, p. 1). In a company with the best machinery on the market, for example, TFP would be high compared to a similar company with no machinery at all as the company with the best machinery would get more value out of the same labor and capital investments.

FIGURE 12 shows us how manufacturing, accommodation and social services faired from a TFP-growth perspective. As noted in the methodology chapter, the EU KLEMS data on this variable only go back to 1996 because Eurostat or the European National Statistical Institutes only began registering this variable in 1995.



FIGURE 12 – RELATIVE TFP GROWTH IN MANUFACTURING, SOCIAL SERVICES AND ACCOMMODATION

Source: Data extracted from Jäger (2018) and processed by the author.

Manufacturing increased its rate of TFP growth in the period while social services stayed very much on the same level of TFP growth throughout the period. Accommodation's TFP growth was decreasing quite dramatically throughout the period. Note that this is not to say that social services and accommodation did not improve their TFP but rather that the rate of improvement was respectively stable or decreasing while manufacturing's TFP growth-rate improved. These finding support the argument that technological change and transitions to increased automation-levels could be important factors when explaining the declining employment numbers in manufacturing.

Throughout these comparisons, we have seen significant differences between the sectors with all tests supporting, or at least not contradicting, the claim that exposure to technological change is an important factor when explaining trends in employment and productivity.

4.2.2 Independent Samples Test

Concluding the comparative part of the analysis, two tables present the results of a statistical comparison of the average yearly growth rate in the six variables used in the previous section for manufacturing and agriculture in one group (high exposure to technological change) and social services and accommodation (low exposure to technological change) in a second group. Agriculture is included in this test because we, in section 4.2.1 and Appendix 2, conclude that similarities between trends within manufacturing and agriculture exist and because the independent samples test becomes increasingly interesting with more cases. The test was done by computing the average annual percentual change for each year, for each variable, and for each sector. In IBM's program SPSS's, the command 'analyze => compare means => independent samples test' was then executed and the below two tables produced. This test was done to assess whether the differences in the trends described in the previous section can be claimed to be statistically significant.

TABLE 1 – COMPARING YEARLY CHANGE RATE MEANS IN MANUFACTURING & AGRICULTURE WITH CHANGE RATE MEANS IN SOCIAL SERVICES & ACCOMMODATION

Group Statistics					
Annual average change in	Is high-exposure	Ν	Mean	Std. Deviation	Std. Error Mean
persons engaged	ves	2	-2,0435	1,12501	,79550
	no	2	1,4575	,49002	,34650
value added, price indices	yes	2	1,5660	2,49184	1,76200
	no	2	4,9235	1,04581	,73950
TFP growth	ves	2	2,5330	1,17663	.83200
	no	2	-,8435	1,16602	,82450
hours worked per week	ves	2	-,4060	,37901	.26800
	no	2	-,3325	,16334	,11550
value added per hour worked	yes	2	5,0800	2,84257	2,01000
	no	2	-,1755	,92985	,65750
output, price indices	ves	2	2,3865	,91005	,64350
	no	2	4,0500	,05657	,04000

Source: Data extracted from Jäger (2018) and processed by the author.

TABLE 2 – INDEPENDENT SAMPLES TEST

Annual average change in	t-test for Equality of Means							
		df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference		
	t					Lower	Upper	
persons engaged	-4,035	1,366	,102	-3,50100	,86769	-9,50091	2,49891	
value added, price indices	-1,757	1,342	,278	-3,35750	1,91089	-16,9609	10,2459	
TFP growth	2,883	2,000	,102	3,37650	1,17133	-1,66374	8,41674	
hours worked per week	-,252	1,359	,834	-,07350	,29183	-2,10841	1,96141	
value added per hour worked	2,485	1,212	,207	5,25550	2,11481	-12,7108	23,2218	
output, price indices	-2,580	1,008	,234	-1,66350	,64474	-9,70875	6,38175	

Notes: Equal variances not assumed. Levene's test for equality of variances requires at least three cases in each group and could therefore not be conducted as our test includes two sectors in each grouping. Source: Data extracted from Jäger (2018) and processed by the author.

Since none of the significance levels are below ,050, the differences between the high-exposure group of sectors and the low-exposure group cannot be said to be

statistically significant from this test. Yet, given that the sample size is very small (only four cases) this does not mean that we should discard our previous observations. Would the same test be run with cases from more European countries from the EU KLEMS dataset, it is likely that one would see falling significance levels as the number of cases increased. This would certainly be interesting to do in another research project. This thesis, however, keeps its focus on Denmark and the four focus sectors.

The variables for persons engaged and TFP growth are the variables where the difference between high and low exposure sectors is most prominent as the test reveals a relatively low significance level of 0,102. There is only a 10,2% chance that the variances between the groups within persons engaged and TFP growth are random. The mean difference is equally high for value added, but here, a high standard error difference indicates large internal differences within the groups, reducing the significance level. On the other end of the spectrum, the variances within the variances worked per week is 83,4% certainly random variation and the internal variance is also the greatest within this variable.

Focusing on the column describing mean differences reveals statistically, as section 4.2.1 did visually, that there were important differences between the two groups in period. The difference between the high-exposure and low-exposure groups in annual percentual change in gross value added per hour, for example, was a full 5,3 percentage points and reached a certainty level of 79,3% (1 - 0,207). The low significance level is due to the fact that the internal variation between the high-exposure sectors was also great, varying from 3,1% in manufacturing to 8,0% in agriculture. The three other variables where mean differences is quite similar are employment (-3,5), TFP growth (3,4), and gross value added (-3,4). If our assumptions on the sectors' levels of technological exposure hold true, this means that especially the three variables discussed here together with value added per hour worked are variables where the sector trends over decades depend very much on technological change.

Note also that, in alignment with the results from **FIGURE 9** the growth in gross value added are higher in the low-exposure groups than in the high-exposure groups which, nevertheless, do astonishingly well within this variable considering the dramatic drops in employment experienced simultaneously.

For further research on this topic, the independent samples test above suggests that if one identifies a sector with *relatively* high annual growth in TFP growth and value added per hour worked while the same sector exhibits *relatively* high negative growth in employment, it is likely that this sector is highly exposed to technological change.

4.3 The Case of Denmark – Offshoring

To further discuss the role of technological change in job losses in the focus sectors, it is relevant to insert the sparse data available on offshoring from Denmark to other countries. Unfortunately, this appears to be a variable with little interest surrounding it; what is provided by Statistics Denmark (2019) is a mere glimpse into offshoring in two recent periods (2009-2011 and 2014-2016) displayed in **FIGURE 13.**



FIGURE 13 – JOBS SOURCED INTERNATIONALLY FROM DENMARK

Source: Statistics Denmark (2019): ORGOUT20. Data processed by the author.

From the chart we can conclude a significant reduction in overall offshoring of jobs, especially due to a reduction in jobs within the combined sector 'Manufacturing, Mining and Quarrying, and Utility Services'. It must however be noted that the 2009-2011 period could be also expected to show a higher level of offshoring given that those years were still the aftermath of the economic recession of the late 2000s. We cannot conclude anything about the direction of the trend from a two-point

insight. It could theoretically be the case that the period 2017:2019 experienced booming offshoring. We are simply too much in the dark. The insight **FIGURE 13** does give us, however, is that significant offshoring was taking place and jobs seem to have been mainly offshored from the manufacturing, mining, and utility sectors.

The EU KLEMS dataset provides us with overlapping information about how many jobs disappeared in the manufacturing, mining, and utility sectors in the period 2009:2011. From 2009 to 2011, the amount of people engaged in these three sectors fell from 346.000 to 315.000, a drop of 31.000. In the same period, Statistic Denmark reports that 10.711 jobs were sourced internationally from these sectors. The number we do not know in this calculation is the number of jobs created within the sectors. With that, we could get better sense of offshoring's importance. As it is, we do not know how many people lost their jobs – we only know the net result of job creation/destruction in the sectors. It is reasonable to assume that jobs have been created in new niches of these sectors and, as McKinsey & Company (2017) points out, that automation and technological advancements have kept some jobs on Danish soil instead of being offshored – through so-called backshoring. The above findings thus suggest that these employment-positive trends have been overrun by the pressure of automation and offshoring combined in the focus sectors of this thesis.

Another thing we do not know is in which of the three sectors combined in one entrance by Statistics Denmark the offshoring happened. It could theoretically be the case that all offshoring happened in the mining sector – although, given the nature of manufacturing, it seems like a better guess than mining.

Nevertheless, we must conclude that it appears to be the case that offshoring plays a significant role in the diminishing employment numbers of manufacturing. This warns us against making unripe conclusions of technological change being the main driver of change. Further elaborations on the issue of offshoring has been omitted from this thesis since it is an immense topic of its own.

4.4 The Case of Denmark – Concluding remarks

In this section, we briefly summarize and discuss the findings of the case study of Denmark. The above analysis presented data on what is thought to be a sector with high exposure to technological change and two sectors thought to have experienced relatively low exposure to technological change. We saw that some trends in manufacturing were different and, in some cases, opposite of the two low exposure sectors. TABLE 3 summarizes the findings for manufacturing.

TABLE 3 – SUMMARY, TRENDS IN DANISH MANUFACTURING

Increasing	Decreasing					
Gross output/gross value added	Employment (persons engaged)					
Productivity (value added/hour worked)	Hours worked per week (only slightly					
	decreasing)					
TFP growth (value added/hour worked						
based)						

Gross value added per hour

If the Danish manufacturing sector has experienced significant automatization in the last four decades, these trends are thus the outcome. However, we do not know exactly which other factors have had a role in the formation of these trends. The analysis of this thesis is like a truck turning right in a traffic light, unable to see the blind angles in the rear mirrors. The blind angles of the analysis, i.e. the factors which the analysis could not present data on, are mostly related to offshoring, skill demand, and managerial productivity increases. It therefore becomes a take-home point of the case study that registering changes in these variables is paramount to the understanding of technological change's effect on labor markets. Without data on these blind angles, it becomes impossible to conclude anything on technological change's effect on labor markets in a precise and certain way.

5 Discussion and Conclusion

While the literature review in the beginning of this thesis presented a range of different sources discussing the effects of technological change on labor markets and society in general, the case study of Denmark exhibited trends within the Danish labor market and within three selected sectors with respectively high and

low assumed exposure to technological change. Having gone through both literature review and case study, we are now somewhat better prepared for a qualified discussion of the research questions of this thesis.

To be sure, the Danish labor market does not yet find itself in an end-of-work crisis as described by Jeremy Rifkin (1995).

The working-age population to

RQ reminder:

Howhastechnologicalchangesince1975affected(1) the Danish Labor market ingeneraland(2)specificsectorsDenmark with highexposuretotechnologicalchange?

unemployment ratio is on the contrary in decline, as seen in the case study. However, this is not to say that nothing is changing. As described by several authors (Andersen et al., 2017; Arlbjørn & Mikkelsen, 2014; Goos et al., 2014; IDA, 2018; McKinsey & Company, 2017; OECD, 2018; World Bank, 2019a), significant changes are happening – also in Denmark. To begin with, the Danes as an organism are, in general, working less hours while increasing their GDP. This is of course in accordance with the expectations of constant productivity increases – partly due to technological advancements.

Secondly, changes in offshoring appears to be a key discussion point when regarding a country like Denmark. Do technological developments destroy jobs domestically or do they save jobs from being offshored? By applying new technology, can Denmark 'steal' jobs from the low-wage offshoring destinations? The answer is most probably that both trends are happening at the same time. In the case study, we saw documentation from Statistics Denmark (2019) which showed

that in some periods, Denmark lost thousands of jobs, especially in manufacturing, to international offshoring.

At the same time, many of the 565 member-companies included in the research of IDA (2018) reported that they saw technology saving jobs from being offshored. McKinsey & Company (2017) and Arlbjørn & Mikkelsen (2014) also stressed the importance of this point. Simultaneously, the case study showed how sectors like agriculture and manufacturing has experienced employment numbers (and total hours worked) in free fall since the 1970s while productivity and value outputs has continued to rise. Some of these changes are most likely the result of new machines, computers, software, and other types of technological developments, especially when considering that the two case-sectors, accommodation and social services, who are assumed to have been less exposed to technological change did not experience the same trends.

While all of this might be happening, spillover effects and demand-increases caused by technological innovation and productivity increases feeds back into the labor demand mechanisms according to some scholars (Andersen et al., 2017; Autor & Salomons, 2017; Gregory et al., 2016; McKinsey & Company, 2017; Vermeulen et al., 2018), creating an upward pressure on labor demand on a general, societal level.

The confusing reality, therefore, might be that, in the case of Denmark, (1) technological advancements obsolete jobs in some sectors while (2) saving jobs from being offshored in some sectors, (3) creating new kinds of jobs in some sectors, and (4) creating increased demand and spillover effects in society in general. Four different, but not mutually exclusive, trends. In **FIGURE 14** below, this is added to the figure we saw in the analysis describing downward pressures on employment (**FIGURE 6**).



FIGURE 14 - SOME FORCES ON EMPLOYMENT, CONTINUED

This situation has been the reality in Denmark in the last 40 years. The analysis has provided insight into the trends in this period, in a way which have not yet been done before, identifying key variables related to technological change on a countryspecific sector-level revealing how sectors with high assumed exposure to technological change have developed in significantly distinct ways during these decades compared to sectors with low assumed exposure to automation. This is particularly true for the variables relating to employment, value added per hour, value added, and TFP growth as section 4.2.1 and 4.2.2 showed.

The analysis, in combination with the literature review, has not revealed a situation in Denmark of imminent catastrophic effects stemming from technological change. On the contrary, much of the literature and some of the data suggest that technological change is indeed affecting the Danish labor market and many other Western labor markets in a predominantly positive way. However, if one dares to look forward, could it be that Denmark is simply approaching the very edge of a technological cliff and that, unsurprisingly, the road towards the edge has not given indications of end-of-work scenarios? The vast majority of the literature reviewed in this thesis has been categorized outside Group A. That is to say, the vast majority of the literature does not support the idea that we are moving towards a future with no or very few jobs for humans. Reviewing the literature, one gets the sensation that it is easiest to find literature which position its arguments somewhere in between the end-of-work alarmist arguments in one end of the spectrum and the tech-optimistic arguments in the other end of the spectrum. This mid-spectrum group repeatedly highlights the importance of institutional adjustments to a changing labor market and stresses the risk of increasing inequality if some population groups fall behind in the race for 'the right' skills.

As seen in the section with literature relating to technological change and Denmark, the McKinsey & Company reports are extensive attempts at assessing which skills will be most needed in Denmark in the near future. The reports encourage policy makers to be aware of the danger of a group of 250.000-300.000 workers in Denmark being skilled for jobs that no longer exist in that near future. At the same time, the reports indicate that there is a lack of supply for some groups of skilled workers. Again, the trends for technological change's effect on labor markets appear to be less unidirectional than presented in public media where the phrase 'robots will take over our jobs' is used on a daily base. Having said that, the case study of four Danish sectors (including agriculture), revealed that certain sectors in

Denmark have certainly been going through dramatic changes in the period under study, posing serious personal challenges for workers within these sectors. With falling labor demand in manufacturing and agriculture, some workers have been pushed towards work in other sectors. However, as the McKinsey reports conclude, workers within high-exposure sectors changing job are likely to choose a job in another high-exposure sector. At one point, these people scrambling around in sectors becoming increasingly dependent on machines and software and increasingly independent on humans, risk running out of job options at one point. Even though the Danish unemployment level has been falling over the last four decades, the potential for a relatively sudden increase of unemployment numbers is indeed there if these workers are not reskilled for jobs in low-exposure sectors.

To tackle problems related to the population groups whose skills are devaluing, many independent sources among the literature reviewed echo the need for educational reform (Autor, 2015; Brynjolfsson & McAfee, 2011; Falk & Biagi, 2017; Frey & Osborne, 2017; Lambert, 2018; Lankisch et al., 2019; OECD, 2018; World Bank, 2019a) to train humans to thrive in a rapidly changing labor market. Having reviewed the case of Denmark, this certainly seems appropriate as we have seen certain sectors, and thus job types, quickly diminishing and changing in the last four decades. This thesis therefore strongly supports educational reforms aimed at injecting skill-flexibility and computer knowledge into the current Danish educational system.

One final note on the results of the analysis revolves around the lack of scientific observation of variables relating to offshoring, skill demand, and managerial productivity increases. This represents a problem for further research in the field since knowledge on these parameters are of crucial importance when evaluating effects technological change because they should be used as control variables. Since these factors are only partially under observance, or not observed at all, it becomes difficult to provide clear answer to the many questions related to technological changes' effect on labor markets. To enable an enlightened discussion on the topic, this thesis recommend that these factors are carefully and systematically observed
so scientists can make more precise conclusions on the effects of technological change which can then be used to either sound the alarm for an approaching of a technologically caused employment cliff-fall or alternatively calm down public worries.

6 References

- Abeliansky, A., & Prettner, K. (2017). Automation and Demographic Change. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2959977
- Adermon, A., & Gustavsson, M. (2015). Job Polarization and Task-Biased Technological Change: Evidence from Sweden, 1975-2005: Job polarization and task-biased technological change. *The Scandinavian Journal of Economics*, 117(3), 878–917. https://doi.org/10.1111/sjoe.12109
- Andersen, J. R., Corydon, B., Staun, J., Jacques, B., Lüneborg, J., & Schröder, P. (2017). A Future That Works The Impact of Automation in Denmark. Retrieved from McKinsey & Company; The Tuborg Research Centre for Globalization and Firms at Aarhus University website: https://www.mckinsey.com/~/media/McKinsey/Locations/Europe%20and %20Middle%20East/Denmark/Our%20Insights/A%20future%20that%20 works%20The%20impact%20of%20automation%20in%20Denmark/A-future-that-works-The-impact-of-automation-in-Denmark.ashx
- Arlbjørn, J. S., & Mikkelsen, O. S. (2014). Backshoring manufacturing: Notes on an important but under-researched theme. *Journal of Purchasing and Supply Management*, 20(1), 60–62. https://doi.org/10.1016/j.pursup.2014.02.003

Autor, D. (2015). Why Are There Still So Many Jobs? The History and Future of Workplace Automation. *Journal of Economic Perspectives*, 29(3), 3–30. https://doi.org/10.1257/jep.29.3.3

Autor, D., & Salomons, A. (2017). Does Productivity Growth Threaten Employment? Retrieved from MIT Department of Economics & Utrecht University School of Economics website: https://pdfs.semanticscholar.org/107b/63fb2e6794dafe06f9cb056f82c1093 253d8.pdf

- Berg, A., Buffie, E. F., & Zanna, L.-F. (2018). Should we fear the robot revolution? (The correct answer is yes). *Journal of Monetary Economics*, 97, 117–148. https://doi.org/10.1016/j.jmoneco.2018.05.014
- Boyd, R., & Holton, R. J. (2018). Technology, innovation, employment and power:
 Does robotics and artificial intelligence really mean social transformation? *Journal of Sociology*, 54(3), 331–345.
 https://doi.org/10.1177/1440783317726591
- Brynjolfsson, E., & McAfee, A. (2011). Race against the machine. Lexington, Massachusetts: Digital Frontier Press.
- Clarín.com. (2018). En 2025 más de la mitad de los puestos de trabajos serán reemplazados por máquinas. Retrieved October 11, 2018, from https://www.clarin.com/sociedad/2025-mitad-trabajos-reemplazadosmaquinas_0_BkBQfET_Q.html

Collier, D. (1993). The Comparative Method. In A. W. Finifter, *Political Science: The State of the Discipline II*. Washington DC: American Political Science Association.

- Comin, D. (2006). Total Factor Productivity. *New York University and NBER*. Retrieved from http://www.people.hbs.edu/dcomin/def.pdf
- Cooper, Y. (2018, August 6). Automation could destroy millions of jobs. We have to deal with it now | Yvette Cooper. *The Guardian*. Retrieved from https://www.theguardian.com/commentisfree/2018/aug/06/automationdestroy-millions-jobs-change
- Creswell, J. W., & Clark, V. L. P. (2017). *Designing and Conducting Mixed Methods Research* (3rd ed.). The United States: SAGE Publications.
- DeCanio, S. J. (2016). Robots and humans complements or substitutes? *Journal* of Macroeconomics, 49, 280–291. https://doi.org/10.1016/j.jmacro.2016.08.003
- EU KLEMS. (2008). EU KLEMS page. Retrieved April 12, 2019, from http://www.euklems.net/project_site.html
- Falk, M., & Biagi, F. (2017). Relative demand for highly skilled workers and use of different ICT technologies. *Applied Economics*, 49(9), 903–914. https://doi.org/10.1080/00036846.2016.1208357
- Fernández-Macías, E. (2012). Job Polarization in Europe? Changes in the Employment Structure and Job Quality, 1995-2007. Work and Occupations, 39(2), 157–182. https://doi.org/10.1177/0730888411427078

Ford, M. (2015). Rise of the Robots. New York, NY: Basic Books.

- Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, 114, 254–280. https://doi.org/10.1016/j.techfore.2016.08.019
- Gallie, D. (2017). The Quality of Work in a Changing Labour Market. *Social Policy*& Administration, 51(2), 226–243. https://doi.org/10.1111/spol.12285
- Gekara, V. O., & Thanh Nguyen, V.-X. (2018). New technologies and the transformation of work and skills: a study of computerisation and automation of Australian container terminals. *New Technology, Work and Employment, 33*(3), 219–233. https://doi.org/10.1111/ntwe.12118
- Gomes, O. (2019). Growth in the age of automation: Foundations of a theoretical framework: Gomes. *Metroeconomica*, 70(1), 77–97. https://doi.org/10.1111/meca.12229
- Goos, M., Manning, A., & Salomons, A. (2014). Explaining Job Polarization:
 Routine-Biased Technological Change and Offshoring. *American Economic* Review, 104(8), 2509–2526.
 https://doi.org/10.1257/aer.104.8.2509
- Gregory, T., Salomons, A., & Zierahn, U. (2016). Racing with or Against the Machine? Evidence from Europe. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.2815469
- Hoffmeyer, A. M. D., & Ma, H. (2018). Automation, Surplus Populations, and the Case of the OECD: A review of the debate on surplus populations and the new wave of automation - is this time different? Retrieved from https://rex.kb.dk/primo-

explore/fulldisplay?docid=RUC_studentstudentproject/6e4f4a70-d193-4733-ad24-841dfb8504a9&context=L&vid=NUI&search_scope=RUC_student&tab= default_tab&lang=da_DK

- Hughes, C., & Southern, A. (2019). The world of work and the crisis of capitalism: Marx and the Fourth Industrial Revolution. *Journal of Classical Sociology*, *19*(1), 59–71. https://doi.org/10.1177/1468795X18810577
- IDA. (2018). Potentialer og barrierer for automatisering og digitalisering i industrien (p. 13). Retrieved from https://ida.dk/media/2624/automatisering_og_digitalisering_i_industrien_2 018_ida_analyse.pdf
- Jäger, K. (2018, July). EU KLEMS Growth and Productivity Accounts 2017 release - Description of Methodology and General Notes [Data bank]. Retrieved from www.euklems.net website: http://www.euklems.net/
- Jericho, G. (2018, May 26). Why the robot revolution risks an economic "death spiral" for Australia | Greg Jericho. *The Guardian*. Retrieved from https://www.theguardian.com/business/grogonomics/2018/may/27/the-imfs-research-on-robots-hits-you-between-the-eyes-with-pessimism
- Kelly, H. (2018, January 29). Robots could kill many Las Vegas jobs. Retrieved October 11, 2018, from CNNMoney website: https://money.cnn.com/2018/01/29/technology/las-vegasautomation/index.html

Keynes, J. M. (1978). The Collected Writings of John Maynard Keynes: The General Theory of Employment, Interest and Money (E. Johnson & D. Moggridge, Eds.). https://doi.org/10.1017/UPO9781139524278

Kujur, S. K. (2018). Impact of Technological Change on Employment: Evidence from the Organised Manufacturing Industry in India. *The Indian Journal of Labour Economics*, 61(2), 339–376. https://doi.org/10.1007/s41027-018-0138-z

- Lambert, D. K. (2018). Workforce Education and Technical Change Bias in U.S. Agriculture and Related Industries. American Journal of Agricultural Economics, 100(1), 338–353. https://doi.org/10.1093/ajae/aax047
- Lankisch, C., Prettner, K., & Prskawetz, A. (2019). How can robots affect wage inequality? *Economic Modelling*. https://doi.org/10.1016/j.econmod.2018.12.015
- le Roux, D. B. (2018). Automation and employment: The case of South Africa. African Journal of Science, Technology, Innovation and Development, 10(4), 507–517. https://doi.org/10.1080/20421338.2018.1478482
- Lenger, A. (2016). The inter-industry employment effects of technological change. *Journal of Productivity Analysis*, 46(2–3), 235–248. https://doi.org/10.1007/s11123-016-0485-z
- Little, T. D. (Ed.). (2013). *The Oxford handbook of quantitative methods*. New York: Oxford University Press.
- Manyika, J., Lund, S., Chui, M., Bughin, J., Woetzel, J., Batra, P., ... Sanghvi, S. (2017). Jobs Lost, Jobs Gained: Workforce Transitions in a Time of

Automation. Retrieved from McKinsey & Company website: https://www.mckinsey.com/mgi/overview/2017-in-review/automationand-the-future-of-work/jobs-lost-jobs-gained-workforce-transitions-in-atime-of-automation

- Mason, P. (2015). *PostCapitalism: A Guide to Our Future*. United Kingdom: Allen Lane.
- McClure, P. K. (2018). "You're Fired," Says the Robot: The Rise of Automation in the Workplace, Technophobes, and Fears of Unemployment. *Social Science Computer Review*, 36(2), 139–156. https://doi.org/10.1177/0894439317698637
- McKinsey & Company. (2017). Automatiseringens effekter på det danske arbejdsmarked (p. 76). Retrieved from McKinsey & Company website: https://www.regeringen.dk/media/4467/hovedrapport-fra-mckinsey-omautomatiseringens-effekter-paa-det-danske-arbejdsmarked-pdf-1.pdf
- Mills, F. C. (1938). Employment Opportunities in Manufacturing Industries of the United States (Bulletin 70). Retrieved from https://www.nber.org/chapters/c3985.pdf
- OECD. (2018). Job Creation and Local Economic Development 2018. OECD.
- Pianta, M. (2018). Technology and Employment: Twelve Stylised Facts for the Digital Age. *The Indian Journal of Labour Economics*, 61(2), 189–225. https://doi.org/10.1007/s41027-018-0124-5

- Piva, M., & Vivarelli, M. (2018). Technological change and employment: is Europe ready for the challenge? *Eurasian Business Review*, 8(1), 13–32. https://doi.org/10.1007/s40821-017-0100-x
- Prainsack, B., & Buyx, A. (2018). The value of work: Addressing the future of work through the lens of solidarity. *Bioethics*, 32(9), 585–592. https://doi.org/10.1111/bioe.12507
- Reijnders, L. S. M., & de Vries, G. J. (2018). Technology, offshoring and the rise of non-routine jobs. *Journal of Development Economics*, 135, 412–432. https://doi.org/10.1016/j.jdeveco.2018.08.009
- Ridley, D. (2008). *The Literature Review: A Step-by-step Guide for Students* (1 edition). London; Thousand Oaks, Calif: SAGE Publications Ltd.
- Rifkin, J. (1995). The End of Work: The Decline of the Global Labor Force and the Dawn of the Post-Market Era. Retrieved from https://eric.ed.gov/?id=ED391963
- Samuelson, P. A., & Nordhaus, W. D. (2010). *Economics* (19th ed). Boston: McGraw-Hill Irwin.
- Schwab, K. (2015, December 12). The Fourth Industrial Revolution. *Foreign Affairs*. Retrieved from https://www.foreignaffairs.com/articles/2015-12-12/fourth-industrial-revolution
- Shewan, D. (2017, January 11). Robots will destroy our jobs and we're not ready for it. *The Guardian*. Retrieved from https://www.theguardian.com/technology/2017/jan/11/robots-jobsemployees-artificial-intelligence

- Slaper, T. F. (2019). Automation and Offshoring in Durable Goods Manufacturing: An Indiana Case Study. *Economic Development Quarterly*, 33(1), 19–38. https://doi.org/10.1177/0891242418807557
- Srnicek, W., & Williams, A. (2015). *Inventing the Future Postcapitalism and a World Without Work*. London, UK & New York, NY: Verso.
- Standing, G. (2017). *Basic Income: And How We Can Make It Happen*. London: Pelican.
- Standing, G. (2018, July 12). The robots coming for your job. *The Economist*. Retrieved from https://www.economist.com/bartleby/2018/07/12/the-robots-coming-for-your-job
- Upchurch, M. (2018). Robots and AI at work: the prospects for singularity. *New Technology, Work and Employment, 33*(3), 205–218. https://doi.org/10.1111/ntwe.12124
- U.S. Bureau of Economic Analysis. (2018, March 15). What is gross output by industry and how does it differ from gross domestic product (or value added) by industry? Retrieved April 23, 2019, from https://www.bea.gov/help/faq/1246
- Vermeulen, B., Kesselhut, J., Pyka, A., & Saviotti, P. (2018). The Impact of Automation on Employment: Just the Usual Structural Change? *Sustainability*, 10(5), 1661. https://doi.org/10.3390/su10051661
- World Bank. (2019a). World Development Report 2019: The Changing Nature of Work [Report]. Retrieved from World Bank website: https://elibrary.worldbank.org/doi/abs/10.1596/978-1-4648-1328-3

World Bank. (2019b). [Data bank]. Retrieved from World Bank Data website: https://data.worldbank.org

Yin, R. K. (2014). Case Study Research: Design and Methods (Applied Social Research Methods) (5th ed.). Retrieved from https://www.amazon.com/Case-Study-Research-Methods-Applied/dp/1452242569

Zhang, P. (2019). Automation, wage inequality and implications of a robot tax. International Review of Economics & Finance, 59, 500–509. https://doi.org/10.1016/j.iref.2018.10.013

7 Appendices

7.1 Appendix 1

EU KLEMS variables. Variables used in this thesis are marked with *.xxxxxxxxx Gross value added at current basic prices (in millions of national currency) Gross Output at current basic prices (in millions of national currency) Intermediate inputs at current purchasers' prices (in millions of national currency) **Compensation of employees (in millions of national currency)** *Number of persons engaged (thousands) Number of employees (thousands) *Total hours worked by persons engaged (thousands) Total hours worked by employees (thousands) *Gross value added, price indices, 2010 = 100 *Gross output, price indices, 2010 = 100 Intermediate inputs, price indices, 2010 = 100 Gross value added, volume (2010 prices) Gross output, volume (2010 prices) Intermediate inputs, volume (2010 prices) *Gross value added per hour worked, volume indices, 2010 = 100 Labour compensation (in millions of national currency) **Capital compensation (in millions of national currency)** Labour services, volume indices, 2010 = 100 Capital services, volume indices, 2010 = 100 ICT capital services, volume indices, 2010 = 100 Non-ICT capital services, volume indices, 2010 = 100

Growth rate of value added volume (% per year)

Contribution of hours worked to value added growth (percentage points)

Contribution of labour composition change to value added growth (percentage points)

Contribution of ICT capital services to value added growth (percentage points)

Contribution of non-ICT capital services to value added growth (percentage points)

Contribution of TFP to value added growth (percentage points)

TFP (value added based) growth, 2010 = 100

Contribution of labour composition change to value added growth (percentage points)

Growth rate of value added per hour worked (% per year)

Contribution of labour composition change to value added per hour worked growth (percentage points)

Contribution of ICT capital services to value added per hour worked (percentage points)

Contribution of non-ICT capital services to value added per hour worked (percentage points)

Contribution of TFP to value added per hour worked growth (percentage points)

*TFP (value added per hour worked based) growth, 2010=100

Growth rate of value added per person employed (% per year)

Contribution of labour composition change to value added per person employed growth (percentage points)

Contribution of ICT capital services to value added per person employed (percentage points)

Contribution of non-ICT capital services to value added per person employed (percentage points)

TFP (value added per person employed based) growth, 2010=100

7.2 Appendix 2

This appendix shows how trends in the sector 'Agriculture, Forestry and Fishing' are very similar to the trends seen in manufacturing. Agriculture being another sector with assumed high exposure to technological change, this appendix thus supports the representability of manufacturing as a high-exposure sector.



 $FIGURE \ 15-COMPARING \ MANUFACTURING \ WITH \ AGRICULTURE$



Source: Data extracted from Jäger (2018) and processed by the author.

The only significant difference from the case of manufacturing is the variable gross value added which boomed in the 1980s for agriculture but then fell to what seems to be a somewhat stable condition around the 2010-level. This does not indicate however, that Danish agriculture is disappearing, but it does indicate that agriculture experience more fluctuations in the amount of value they are able to add – possibly a consequence weather-variations or legislative restrictions. Other variables in the EU KLEMS dataset indicate that indeed, Danish agriculture is not in a disappearing trend, for example the variable on gross output.