The robots are already here

An empirical assessment of automation and changes in the occupational composition of the Norwegian labour market

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Abstract

The threat of automation got enormous attention after Frey and Osborne published their seminal paper in 2013, which examined how susceptible jobs were to computerisation. Their finding that almost half of the jobs were at high risk of being automated over the next two decades, initiated a big debate about whether robots are coming for our jobs. This thesis estimates the relationship between automation probabilities, constructed by Frey and Osborne, and employment share within 348 Norwegian occupations. When considering the time period 2009-2016, I find a negative and significant correlation between the change in occupational employment and automation. This relationship is stronger for women and individuals with secondary education, but in the longer run, men and low-educated individuals seem to be more exposed to the technological advances. My thesis shows that the threat of automation is real, and that upcoming technology could have a bigger labour-saving effect than before. I find also evidence supporting the fact that we are facing restructuring rather than a jobless future. The empirical findings are relevant in the debate about what type of labour and education policies to implement.

Preface

First of all, I would like to thank my supervisor, Simen Markussen. I am truly grateful for his insights, knowledge and great advice. His contribution to the thesis has been invaluable. I would also like to thank *The Ragnar Frisch Centre for Economic Research* for giving me a scholarship and an office space in an inspiring environment. I have been lucky to share this office space with Maria, and would like to thank her for being a great friend to discuss thesis with.

I have had a remarkable time at the University of Oslo, and I am thanking my fellow students and friends for that. I would also like to thank my family for always supporting and encouraging me. Finally, I want to thank Etienne for motivating me and for always believing in me.

Any inaccuracies or errors in this thesis are my own responsibility.

Oslo, May 2018

Dana Darja Øye

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1 Introduction

There have been striking advances in automation, robotics and artificial intelligence. Although previous years have shown that automation has increased productivity and created new jobs, many are now expressing concerns about a noticeable amount of jobs being replaced by robots. *The Economist* wrote an article in 2014 about the "onrushing wave" of automation, pointing out that we might soon face massive unemployment and that policymakers have to start preparing for a robot invasion. The number of robots and the number of tasks they can perform is increasing at a rapid pace. In 2009, Google launched a self-driving car, while in 2011, Watson, a pattern-recognising supercomputer developed by IBM, beat the best human competitors in an American general-knowledge quiz show "Jeopardy". In 2016, IBM Watson showed that it not only could beat humans in quizzes, but also do complex cognitive tasks such as cancer diagnosis and treatment recommendations. The worrying aspect of today's technological changes is that they are exponentially faster and far wider in scope than ever seen before. Some even claim that it is easier to answer the question about what machines cannot do than answer the question about what they can do.

The fear that technology will leave people without jobs is not a new phenomenon. At the beginning of the 19th century, British Luddites, the most well-known technological resistance movement, were concerned about the changes that followed The Industrial Revolution. They feared that their skills would go to waste, and destroyed textile machines as a form of protest. In 1930, Keynes expressed concern by writing "*We are being afflicted with a new disease of which some readers may not yet have heard the name, but of which they will hear a great deal in the years to come – namely, technological unemployment."* But everyone who feared technological unemployment has been wrong. Autor (2015) explains that both commentators and experts tend to emphasize the fact that jobs are being replaced by machines, but forget about the jobs that cannot be replaced. These jobs are often more productive due to technology, and will therefore employ more workers.

Approximately 15 years ago, Autor et al. (2003) suggested that computers were good at performing repetitive routine cognitive and manual tasks, but poor at performing non-routine tasks. 10 years later, a working paper published by Frey and Osborne (2013) examined how automatable different occupations were, and concluded that computerisation is also taking place in non-routine tasks. They came with dramatic predictions about how modern technology will replace individuals in a variety of jobs. Authors Andrew McAfee and Erik Brynjolfsson argue in the book "The second machine age" (2014) that we are facing technological change different from what we have experienced before. Although new technology up to now has led to restructuring and economic growth and not mass unemployment, there is no guarantee that this will also be the case in the upcoming years.

In order to be able to offer right education and retrain those already in the workforce, it is important to know which occupations might disappear and what type of skills might be needed in the future. In relation to this, Norwegian government has set up an expert committee (Government, 2018), who will examine what unmet needs exist for continuing education today and to what extent the education system is able to meet the needs of the workforce for flexible competence offerings. The committee will also examine whether the framework conditions for investment in new skills are sufficiently good for companies and if the individuals have enough opportunities to retrain. The goal is to make everyone qualified for a working life that is constantly changing due to digitalization and new technologies.

This thesis contributes on the on-going discussion on how automation increases unemployment by taking over human´s job. In particular, I will focus on the relationship between automation and the employment change within Norwegian occupations. I will analyse if there is compliance between an occupation having a high probability of being automatized and decreasing employment share in that occupation. For this purpose, I will use probabilities constructed by Frey and Osborne (2017), and in this way assess if they can be used as rough approximations to predict the future of occupations.

My analysis will be done on a sample of employed individuals in Norway in 2009 and 2016, using the software program Stata 15. I expect occupations with high automation probabilities to have declining employment share, while occupations with low automation probabilities to have increasing employment share. I assume to find different threats of automation on gender, education level and age group. Furthermore, by including measures on R&D and Internet, I want to find out if they mitigate or magnify the potential relationship between automation and occupational employment. By identifying if automation is a threat in Norway, we can better understand what type of labour and education policies to implement.

The threat of automation has been discussed for Norway. Pajarinen et al. (2014) converted computerisation probabilities constructed by Frey and Osborne (2013) to Norwegian occupations, and estimated that 33% of all jobs are at high risk of being automated in the next 10-20 years. Fölster (2017) examined how much of lost jobs between 2009 and 2014 were due to automation, and estimated this share to be between 8-9%. My contribution is to look at the relationship between automation and occupational employment in Norway between 2009 and 2016, and analyse which groups are most exposed based on gender, education and age. This will be one of the first studies to test how predictive the automation probabilities constructed by Frey and Osborne are, and the first extensive study to show how these probabilities relate to occupational composition in Norway.

The remainder of the thesis is structured as follows. Section 2 reviews empirical findings from prior studies. Section 3 describes the data and the sample used in the analysis. Section 4 presents statistical evidence showing that automation is a threat in Norway. Section 5 introduces an empirical model for estimating the relationship between automation and the change in occupational employment and shows how strong this relationship is for different individual characteristics. Section 6 argues that my results are not driven by other factors, such as financial crisis, oil price drop and globalisation. Section 7 adds the impact of R&D expenditures and private broadband subscriptions to the model. Finally, section 8 discusses and concludes the results.

2 Literature review

Several authors have tried to estimate what technology will mean for the future, and they don’t seem to agree. While some claim that automation will create more jobs, others argue that automation is a threat to employment. One of the most extensive studies, by Acemoglu and Restrepo (2017), looks at the effects of introducing robots in the US labour market. The exposure to robots is defined as the sum over industries of the national penetration of robots into each industry, multiplied by the employment share of that industry in that labour market. They find that areas that were most exposed to robots, faced a decline in both the employment and the wages. Graetz and Michaels (2017), on the other hand, find no significant relationship between the increased use of industrial robots and overall employment, although they find some evidence that robots may be reducing employment of low-skilled workers. Mann and Püttmann (2017), using patents as a measure of automation, estimate a positive influence on employment in local labour markets. They find a declining manufacturing employment, but state that it is more than compensated by service sector job growth.

Of particular relevance to this thesis, are the papers from Frey and Osborne (2017) and Pajarinen et al. (2014). Frey and Osborne look at how susceptible jobs are to technology by estimating the probability of computerisation for 702 detailed US occupations. They refer to computerisation as job automation by means of computer-controlled equipment. After estimating automation probabilities, they examine expected impact of future computerisation on the US labour market, and find that 47% of the US jobs are at high risk. They also find that low-wage and low-education employees face a higher risk of automation relative to other employees. Pajarinen et al. (2014) convert automation probabilities to Norwegian labour data, and find that 1/3 of Norwegian occupations might be at risk. They also show that low-wage and low-skill occupations appear to be the most threatened by automation. In addition, they point out that service and public sector jobs are relatively more sheltered than manufacturing and private sector jobs.

At the same time, recent studies for OECD countries report a much lower threat of automation. Arntz et al. (2016) find that 9% of jobs are at high risk, while Nedelkoska and Quintini (2018) find that 14% of jobs will be exposed to automation. The same study reports that only 6% of all jobs in Norway have a risk of automation higher than 70%, classifying Norway as one of the safest countries. While Frey and Osborne assume that whole occupations are automated, the studies for OECD countries take into account that people often perform tasks that are hard to automate. Therefore, Arntz et al. (2016) argue that the approach taken by Frey and Osborne (2013) might lead to an overestimation of jobs automatability and illustrate this by using retail salespersons as an example. According to Frey and Osborne (2013), people working in this occupation face an automation potential of 92%. Arntz et al. (2016) argue that only 4% of retail salespersons perform their jobs with neither both group work nor face-to-face interactions, concluding that this occupation should have a much lower automation probability. A weakness with Arntz et al. is that they don´t take into account that customers might become less interested in face-to-face meetings with sales people, thus making interaction a less important task of retail salespersons. This have already taken place in travel agencies, where a large share of individuals who spent time talking to customers, have now been replaced by digital travel booking.

Literature on automation emphasizes how technological unemployment has led to more polarized labour markets in most countries. More low-skilled and high-skilled occupations have been observed for the United States (Autor et al., 2006; 2008), the United Kingdom (Goos and Manning, 2007) and the European countries (Goos et al., 2014). These studies show growing employment in professional, managerial and personal services occupations, and declining employment in manufacturing and other routine jobs. Several explanations have been put forward. Blinder (2009) mentions offshoring as an important reason for the change in the job structure in the richest countries. Another explanation is based on the link between job polarization and wage inequality. According to Manning (2004) and Mazzolari and Ragusa (2013), the rise in the share of income going to the rich in the United States and the United Kingdom may have led to an increase in demand for low-skilled workers whose employment increasingly consists of providing services to the rich. The main hypothesis put forward to explain job polarization, however, is the routinization hypothesis (Autor et al., 2003; Autor and Dorn, 2013). These authors argue that computer capital substitutes for workers in performing cognitive and manual tasks that can be accomplished by following explicit rules, and complements workers in performing non-routine problem-solving and complex communication tasks. They explain that the effect of technological progress is to replace routine labour which tends to be clerical and craft jobs in the middle of the wage distribution.

The increasing R&D expenditures and broadband subscriptions might be fuelling the current automation wave. A study by Bogliacino et al. (2012), which is the first attempt to assess the impact of R&D expenditures on employment in a European context, finds a positive and significant employment effect of R&D expenditures in high-tech manufacturing and service sectors. Same results are found in Piva and Vivarelli (2017). By using data on adoption of broadband Internet in Norwegian firms over the period 2001-2007, Akerman et al. (2015) find that Internet improves the labour outcomes and productivity of skilled workers, while it worsens for unskilled workers. They argue that broadband adoption in firms complements skilled workers in executing non-routine abstract tasks, and substitutes for unskilled workers in performing routine tasks. The finding that the access to broadband has only positive employment effects for skilled workers has also been found in Falck (2017).

3 Data

3.1 Automation probabilities

I want to analyse the relationship between the threat of technological advances and the change in occupational employment in Norway. To assess this, I need a measure of technological advances. Common measures, that are widely used in the empirical literature, are R&D expenditures, number of patent applications and the enhancement of ICT. Historically, automation has been limited to manual and cognitive routine tasks (Autor et al., 2003; Autor and Dorn, 2013). Recent technological breakthroughs, however, have made computerisation spread to also non-routine tasks. These new technologies are not easily captured by the "standard" technology measures. I have thus chosen to use probabilities, constructed by Frey and Osborne (2017), as the measure for automation. Fölster (2017) and Hessel et al. (2018) are some of the studies that have based their analysis on these probabilities. Fölster (2017) uses them to capture how well the automation risk according to Frey and Osborne (2013) explains employment change in occupations in Norway. Hessel et al. (2018), uses them to quantify the extent to which health characteristics of workers are related to potential risk of experiencing job displace due to automation in Norway.

3.1.1 Method used in Frey and Osborne

Frey and Osborne use O*NET data from 2010 to construct automation probabilities, which are used as a measure for technological advances in my analysis. O*NET defines the key features of an occupation as a standardised and measurable set of variables, and also provides open-ended descriptions of specific tasks to each occupation. The 2010 version of O*NET contains information on 903 detailed occupations, most of which correspond closely to the Labour Department's Standard Occupational Classification (SOC). O*NET classification is somewhat more detailed, and Frey and Osborne aggregate these occupations to correspond to the 6-digit SOC classification. In addition, they exclude any 6-digit SOC occupations for which O*NET data was missing. Doing so, they end up with a final dataset consisting of 702 occupations.

Frey and Osborne's analysis builds on Autor et al. (2003), where the job tasks were divided along two dimensions: cognitive vs manual and non-routine vs routine. They redefine this model by assuming that technological advances are increasingly capable of performing non-routine cognitive tasks such as legal writing or driving. Frey and Osborne note that especially advances in Machine Learning (ML) and Mobile Robotics (MR) will take over certain tasks previously confined to non-routine jobs. The only domains of tasks that appear to be exempt from this automation threat are tasks related to perception and manipulation, creative intelligence and social intelligence. Frey and Osborne identify these domains as technology bottlenecks. It is for now impossible for computers or robots to take over tasks related to these bottlenecks due to difficulties in orientating in complex surroundings, developing new and complex ideas and responding intelligently and empathically to human counterparts.

Table 1: Computerisation bottlenecks and O*NET variables. Source: Frey and Osborne (2017).

	Variable	Definition
Perception manipulation	Finger dexterity	The ability to make precisely coordinated movements of the fingers of one or both hands to grasp, manipulate, or assemble very small objects.
	Manual Dexterity	The ability to quickly move your hand, your hand together with your arm, or your two hands to grasp, manipulate, or assemble objects.
	Cramped work space, awkward positions	How often does this job require working in cramped work spaces that requires getting into awkward positions?
Creative intelligence	Originality	The ability to come up with unusual or clever ideas about a given topic or situation, or to develop creative ways to solve a problem.
	Fine arts	Knowledge of theory and techniques required to compose, produce, and perform works of music, dance, visual arts, drama, and sculpture.
Social intelligence	Social perceptiveness	Being aware of others' reactions and understanding why they react as they do.
	Negotiation	Bringing others together and trying to reconcile differences.
	Persuasion	Persuading others to change their minds or behaviour.
	Assisting and caring for others	Providing personal assistance, medical attention, emotional support, or other personal care to others such as co-workers, customers, or patients.

Frey and Osborne construct probabilities in two steps. In the first step, they choose 70 out of 702 occupations, which they consider as either fully automatable or not automatable at all. For this purpose, Frey and Osborne attend a workshop held at Oxford University’s Engineering Sciences Department, where they together with other experts examine automatability of a wide range of tasks. An occupation is assigned 1 if it is completely automatable, and 0 if not. This assignment is based on eyeballing the O*NET tasks and job description of each occupation, and is done by answering the question “*Can the tasks of this job be sufficiently specified, conditional on the availability of big data, to be performed by state of the art computer-controlled equipment*”. Thus, the numbers 0 and 1 are only assigned to occupations which they are most confident about.

In the second step, Frey and Osborne examine whether this subjective classification is related to nine objective O*NET variables, most likely to serve as indicators of bottlenecks to computerisation. These variables, together with a description, are listed in Table 1. To assess this, they estimate different variants of a probabilistic model. They find a high predictive power between the nine O*NET variables and occupation´s automatability. By using the probabilistic function which gives the most accurate classification, they predict the probability of computerisation for all occupations. This final procedure mitigates some of the subjective bias from hand-labelling the 70 occupations, reducing the risk of this bias affecting their analysis.

The complete list of occupations and their automation probabilities, with all the 70 key occupations listed, can be found in the Appendix A in Frey and Osborne (2017). It is important to note that the authors focused on the impact of computerisation on the mix of jobs that existed in 2010, and their analysis is thus limited to substitution effect of future computerisation. The method used ignored both that the content of tasks within occupations and the mix of occupations are constantly changing. It also did not take into account the social forces that might be slowing down technological advances. Even though there are some concerns, the automation probabilities are useful to gain qualitative and to some degree quantitative understanding of how technology will impact occupational structures in the future. They should, however, be treated as approximations, and not exact truths.

3.1.2 Conversion of automation probabilities to Norwegian occupations

Pajarinen et al. (2014) converted probabilities defined for the US occupations in Frey and Osborne (2013) to International Standard Classification of Occupation (ISCO-08). Due to differences in the two classification systems, the number of occupations dropped to 374 in the Norwegian case. Furthermore, Pajarinen et al. (2014) omitted occupations with less than 20 workers, and their final list consisted of 358 occupations.

By moving from the United States classification to the International classification, Pajarinen et al. (2014) were forced to sum up some occupations. Their main concern was thus how well US probabilities applied to the Norwegian labour market. To assess this, they used data for 2012, and estimated how much of the US employment was in the high-risk category for different classifications. Pajarinen et al. (2014) found that 49% of US employment was in the high-risk category when using SOC. When changing the occupation classification to ISCO, they found that 45% of US employment was in the high-risk group. They concluded that due to this modest fall in the share, their analysis should not suffer from conversion problems between SOC and ISCO classifications.

3.1.3 Data on automation probabilities

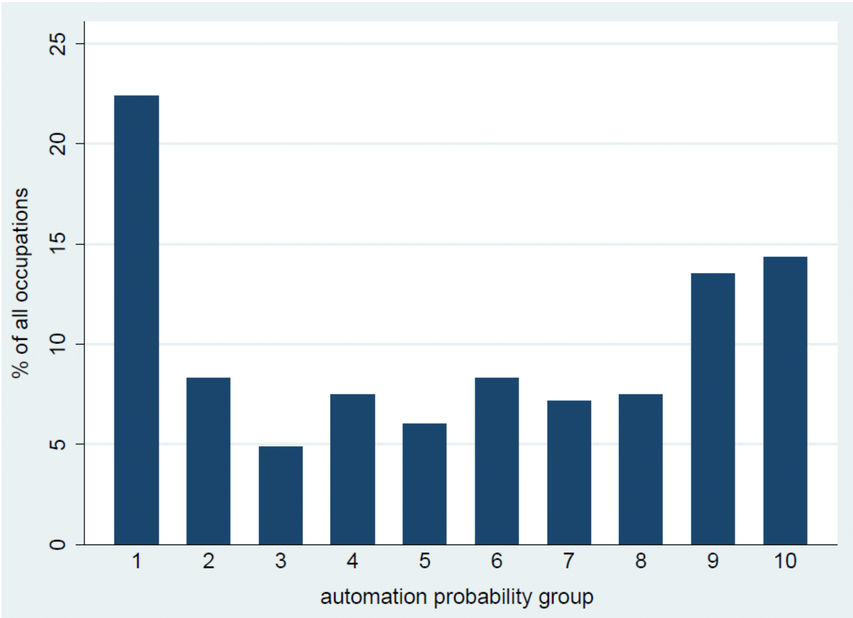
My dataset consists of detailed information about employed individuals in Norway, where each employee is registered with an occupation code. Employers use the occupation directory to report the profession of their employees. The occupation directory is based on Standard for Occupational Classification from 1998, STYRK-98, and all job titles are reported as 7-digit codes. When Statistics Norway publishes the numbers, they follow a newer standard from 2008, STYRK-08, where job titles are reported as 4-digit codes. I use code list for occupation directory, downloaded from Statistics Norway, to convert the occupation codes in my dataset to a 4-digit STYRK code. After that, I merge my data with the data from Appendix 3 in Pajarinen et al. (2014). This is straightforward since the structure of ISCO-08 and STYRK-08 is the same and matches down to the 4-digit level.

Originally, there is data on automation probabilities for 358 Norwegian occupations. When merging with my dataset, I'm left with 348 occupations. The first reason for this is that individuals in my dataset are not employed in eight of the occupations[1] listed in Pajarinen et al. (2014). The second reason is that two of the occupations[2] behave abnormally, making a big, sudden jump between years 2014 and 2015. These occupations have a low automation probability and huge employee increase, and to make sure they don't drive my results, I exclude them from my dataset.

[1] Individuals in my dataset are not employed, either in 2009 or 2016 or both years, in these eight occupations: stationary plant and machine operators not elsewhere classified, shopkeepers, computer network professionals, other artistic and cultural associate professionals, air traffic safety electronics technicians, prison guards, street vendors (excluding food) and judges.

[2] The two occupations that behave abnormally in my dataset are policy administration professions and university and higher education teachers.

Figure 1: The distribution of occupations over the probability of automation.



In Figure 1, occupations are sorted in 10 groups, depending on their automation probability. The first group consists of occupations with automation probability between 0.001 and 0.099; the second group consists of occupations with automation probability between 0.1 and 0.199, and so on. The vertical axis measures the share of occupations belonging to a specific automation probability group. We can see a form for polarization in the figure, with the highest number of occupations in the first and the last group. There are 78 occupations that have a small risk of being exposed to automation, accounting for approximately 22% of all occupations. The number of occupations that have a high risk of being exposed to automation is 50, accounting for approximately 14% of all occupations. This means that workers are typically quite sheltered from or quite threatened by automation, rather than somewhere in between.

Frey and Osborne categorize occupations into three categories, depending on the risk: low risk, medium risk and high risk. They define low risk occupations to have automation probabilities up to 0.3, high risk occupations to have automation probabilities above 0.7, and medium risk occupations to have automation probabilities between 0.3 and 0.7. Furthermore, they believe that high risk occupations could be exposed for automation within one or two decades. Low risk and medium risk occupations, however, face technology bottlenecks, and it might take even longer time for these occupations to face the threat of automation. Frey and Osborne (2017) state that 47% of jobs in the US are at high risk to become automatized in the next two decades. Following their classification of the occupation groups, my data shows that approximately 35% of jobs in Norway are at risk of disappearing within the next two decades.

3.2 Norwegian labour market data

3.2.1 Employment data

As mentioned above, I have microdata on all employed individuals in Norway, giving me employment in 348 occupations. To assess the relationship between automation and change in occupational employment, I consider years 2009 and 2016. Year 2009 was chosen since Frey and Osborne (2013) started to construct their automation probabilities in 2010, and year 2016 was chosen due to being the last year I have microdata for. I restrict my dataset to include workforce, keeping only individuals in the age group 15-74. To reduce "noise" in my analysis, I only keep individuals who earn more than twice the basic amount[3] in the relevant year. This is done to exclude individuals who have been working for a limited time period.

Table 2: Summary statistics.

	Obs	**Mean**	**Std. Dev.**	**Min**	**Max**
Automation probability	348	0.49	0.34	0.00	0.99
Employment share[4]					
2009	348	0.00	0.01	0.00	0.05
2016	348	0.00	0.01	0.00	0.04
Monthly wage					
2009	348	35061.19	11243.42	18136.01	94978.79
2016	348	44372.93	12185.78	23575.39	100499.96
Occupational employment growth					
All	348	0.17	0.81	-1.63	8.45
Men	347	0.18	0.85	-1.51	8.78
Women	344	0.20	0.81	-1.78	7.97
Lower education	343	0.01	0.78	-2.83	5.28
Secondary education	344	0.09	0.70	-1.81	5.70
Higher education	341	0.30	0.84	-1.61	9.04
Age: 15-40	347	0.05	0.88	-1.79	8.58
Age: 41-74	348	0.26	0.79	-1.77	8.32

[3] National Insurance scheme "G" defines yearly basic amount, which is 72 881 NOK in 2009, and 92 576 NOK in 2016.

[4] Variable *employment share* is defined as $\frac{number\ of\ employees\ in\ occupation\ i}{total\ number\ of\ employees}$.

My dependent variable is *occupational employment growth*, which is defined as follows:

$$occupational\ employment\ growth = ln\ \frac{number\ of\ employees\ in\ occupation\ i\ in\ 2016}{number\ of\ employees\ in\ occupation\ i\ in\ 2009}$$

This variable measures the employment growth rate in each occupation. Looking at the whole dataset, it ranges from -1.63 to 8.45, meaning that some occupations in my dataset have increased enormously. The big increase might also be due to the measurement error, where the number of employees in these occupations was either underreported in 2009 or overreported in 2016. To correct for this potential error, I restrict employment growth to be between -2 and 3, changing five values. I am also interested in looking at the changes in the employment growth for different individual characteristics, such as gender, education level and age. Therefore, I define seven additional dependent variables; occupational employment growth for men, women, lower education, secondary education, higher education, age 15-40 and age 41-74. All these variables will also be restricted between -2 and 3 in my regressions.

My independent variable is *automation probability*, which is defined as the probability of computerisation for each occupation, computed by Frey and Osborne (2013), and converted for Norwegian occupations by Pajarinen et al. (2014). The lowest automation probability is 0.004, rounded up to 0.00 in Table 2, and the highest automation probability is 0.99. The average automation probability of all the 348 occupations is 0.49.

3.2.2 Gender, education and age

I have data in the individual´s education level only up to including 2015. Since 2016 is my year of interest, I assume that education levels in 2015 are still valid in 2016. This is a reasonable assumption since it usually takes more than one year to go from one education level to another. According to Norwegian standard for education grouping, there are nine levels, plus an unspecified value. I combine these levels into three main groups: lower education, secondary education and higher education. The groups and levels are classified in Table 3.

Table 3: Classification of education.

Education	**Level**	**Level name**
Lower education	0	No education and pre-school education
	1	Primary education
	2	Lower secondary education
	9	Unspecified
Secondary education	3	Upper secondary, basic
	4	Upper secondary, final year
	5	Post-secondary not higher education
Higher education	6	First stage of higher education, undergraduate level
	7	First stage of higher education, graduate level
	8	Second stage of higher education (postgraduate education)

Table 4: Share of employees when the sample is divided according to gender, education group and age.

	Share in 2009	Share in 2016
Gender		
Women	44.47	45.25
Men	55.53	54.75
Education group		
Lower education	19.01	16.05
Secondary education	47.86	44.41
Higher education	33.13	39.54
Age group		
Age: 15-40	44.00	39.98
Age: 41-74	56.00	60.02

My sample consists of 1 539 824 individuals in 2009 and 1 687 528 individuals in 2016. As mentioned above, I only consider employees in the age range 15-74, with wage above twice the basic amount in the given year. Both in 2009 and 2016, men account for a larger employee share than women; there are approximately 10% more men in both years. Furthermore, there are many more individuals in the age group 41-74 than age group 15-40. This could be due to a large amount of young people taking secondary and higher education. In 2009, the difference between age groups was approximately 12%, while the difference in 2016 was more than 20%. This is in line with the increasing number of people taking higher education. We can see that in 2009, approximately 33% of individuals in the sample had higher education. This number was almost 40% in 2016. Both the share of individuals with lower education and the share of individuals with secondary education decreased between 2009 and 2016.

3.3 Data on R&D and Internet

My data on R&D and Internet is collected from StatBank Norway. I use intramural and extramural R&D expenditures in the business enterprise sector, measured in million NOK, as a proxy for R&D. The data is collected for the years 2010-2016 in 19 Norwegian counties.[5] Statistics Norway defines intramural R&D expenditures as all expenditures carried out by the company with its own personnel. These expenditures encompass labour costs, cost of hired personnel, other current costs and capital expenditures on R&D. Extramural R&D expenditures are defined as purchased R&D services performed by other entities, such as research institutes and other Norwegian or foreign enterprises. The R&D data is collected by a survey, which includes all companies with at least 50 employees and companies with 10-49 employees which reported considerable R&D activity previous year. Statistics Norway report that the response rate for the survey is quite high, around 95 percent, and for that reason, the results should not be biased by non-respondents.

[5] It is today 18 counties in Norway, as the counties Nord-Trøndelag and Sør-Trøndelag were merged together into one county, Trøndelag, on 1 January 2018. As this change is after my period of interest, it does not affect my analysis.

As a proxy for Internet, I use private broadband subscriptions by percent of households. This data is collected quarterly from 2004 to 2017 in 476 Norwegian municipalities.[6] I exclude data on 53 municipalities, which have missing values in 2009, leaving me with 423 municipalities. Statistics Norway defines Internet subscription as a service that gives end-users access to the Internet. The population in the Internet survey consists of all enterprises that deliver fixed broadband access to the Internet to end-users in Norway. Since these enterprises do not have to register, some minor suppliers of Internet access might be missing from the sample. Measured in proportion to the total amount of respondents, the response rate is about 95 percent, the same as for R&D expenditures.

3.3.1 R&D

Table 5: Summary statistics for R&D variables.

	Obs	Mean	Std.Dev.	Min	Max
Automation probability	5932	0.48	0.34	0.00	0.99
Occupational employment growth	5932	0.26	0.74	-5.00	7.23
R&D variables					
rd10	5932	1329.31	1693.71	13	6866
rd16	5932	2000.37	2279.08	118	8350
diffrd	5932	0.67	0.69	0.04	2.65
rdgrowth	5932	0.57	0.40	0.17	2.21
automation probability x diffrd	5932	0.32	0.47	0.00	2.63
automation probability x rdgrowth	5932	0.27	0.31	0.00	2.18

Variables *automation probability* and *occupational employment growth* are defined as before, except that the dependent variable is now measuring employment growth in each occupation for every county. To correct for measurement errors, I restrict this variable to be between -2 and 3.

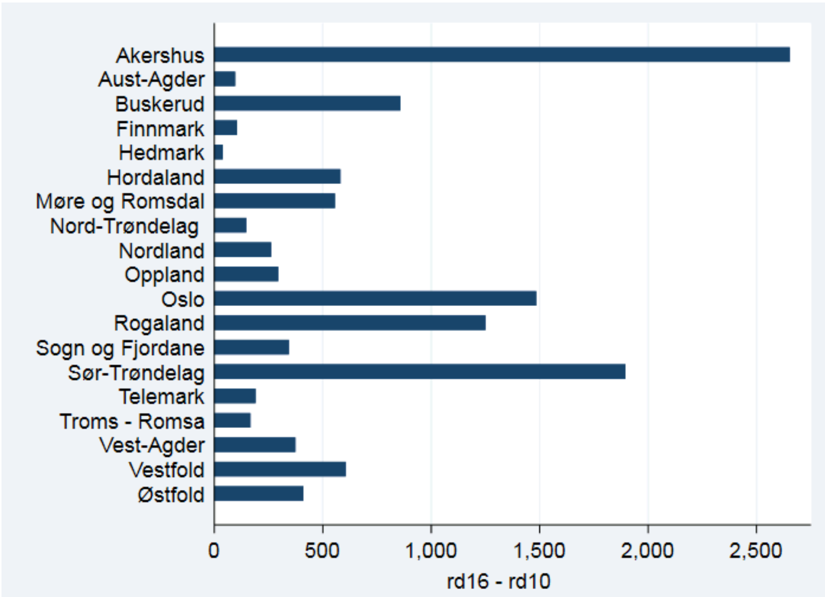
I have data on intramural and extramural R&D in the business enterprise sector for the years 2010-2016. I want to continue to analyse the changes in employment between 2009 and 2016, and make thus assumption that data for 2010 is also valid for 2009. This assumption is reasonable, taking into account that investments in R&D have been increasing the past years, indicating that intramural and extramural R&D should be lower in 2009 than 2010 or

[6] The number of municipalities has been changing from year to year due to municipalities splitting up and merging together. In 2017, there were 426 municipalities in Norway.

approximately the same. Assuming this is true; using R&D data for 2010 instead of 2009 should not have any big impact on my analysis.

Taking the total of intramural and extramural R&D expenditures, I get the total expenditure on R&D for every county. The variable rd10 shows total expenditure on R&D in 2010, while rd16 shows the total expenditure on R&D in 2016. These numbers are measured in million NOK. Both in 2010 and 2016, the county with the smallest expenditure on R&D was Finnmark, while the county with the highest expenditure on R&D was Oslo. Between these years all counties experienced an increase in expenditures on R&D. In Finnmark it increased from 13 to 118 million NOK, while in Oslo it increased from 6866 to 8350 million NOK.

Figure 2: Increase in R&D expenditures for counties. Source: StatBank Norway.



In Figure 2, we can see the increase in R&D expenditures for every county from 2010 to 2016. Some of the counties have experienced enormous increase in R&D expenditures between these years, while others have had a relatively small increase. By using these differences in the expenditures, I can exploit if the occupations in counties with the higher increase in R&D expenditure and high automation probability are the ones with higher decrease in the occupational employment. From the figure, we see that the two counties with the highest increase in R&D expenditures are Akershus and Sør-Trøndelag, while Hedmark and Finnmark are the counties with the smallest increase in the R&D expenditures.

I define R&D expenditures in two different ways:

1) $diffrd = \frac{rd16 - rd10}{1000}$

2) $rdgrowth = ln\ \frac{rd16}{rd10}$

Although there could be other ways of defining the R&D expenditures, these two definitions are the most intuitive in my opinion. The first variable, *diffrd*, is just the difference between R&D expenditures in 2016 and 2010, divided by 1000. This new variable measures the difference in the expenditures on R&D in thousand NOK. The second variable, *rdgrowth*, is defined as the log of the ratio of R&D expenditures in 2016 and 2010. In this way, the independent variable is defined in the same manner as dependent variable. Furthermore, I construct interaction variables between my R&D variables and automation probabilities, named *autoprob x diffrd* and *autoprob x rdgrowth*. This is done to examine how changes in the R&D expenditures, interacted with automation probabilities, relate to occupational employment growth on the county level.

3.3.2 Internet

Table 6: Summary statistics for Internet variables.

	Obs	**Mean**	**Std.Dev.**	**Min**	**Max**
Automation probability	47506	0.45	0.34	0.00	0.99
Occupational employment growth	47506	0.18	0.77	-5.00	7.23
Internet variables					
int09	47506	63.68	9.21	30.10	87.90
int16	47506	80.63	12.57	34.20	216.70
diffint	47506	0.17	0.11	-0.26	1.29
intgrowth	47506	0.24	0.14	-0.56	0.91
automation probability x diffint	47506	0.08	0.08	-0.25	1.26
automation probability x intgrowth	47506	0.11	0.11	-0.55	0.88

Variables *automation probability* and *occupational employment growth* are defined as before, but now the dependent variable measures the employment growth in each occupation for every municipality. I restrict again this variable to be between -2 and 3.

Variables *int09* and *int16* measure private broadband subscription by percent of households. In 2009, the municipality with the lowest subscription percent was Lierne, while it was Træna in 2016. Bykle was the municipality with the highest subscription percent both in 2009 and 2016, with 87.90 and 216.7 percent respectively. There are many cabins in Bykle, and thus more private broadband subscriptions than households. Other municipalities that have an *int16* variable above 100, also have a high share of cabins. Therefore, the increase in the Internet variable in these municipalities might not be entirely due to the technology, but simply due to more cabins with broadband subscription. I will thus restrict all *int16* variables above 100 to equal 100, such that "cabin municipalities" don't drive my results.

In the same way as with R&D expenditures, I will use the difference in private broadband subscriptions, together with automation probabilities, to see what happens with occupational employment on municipality level. There are again several different ways to define the Internet variable. As with R&D expenditures, I use these two definitions:

1) $diffint = \frac{int16 - int09}{100}$

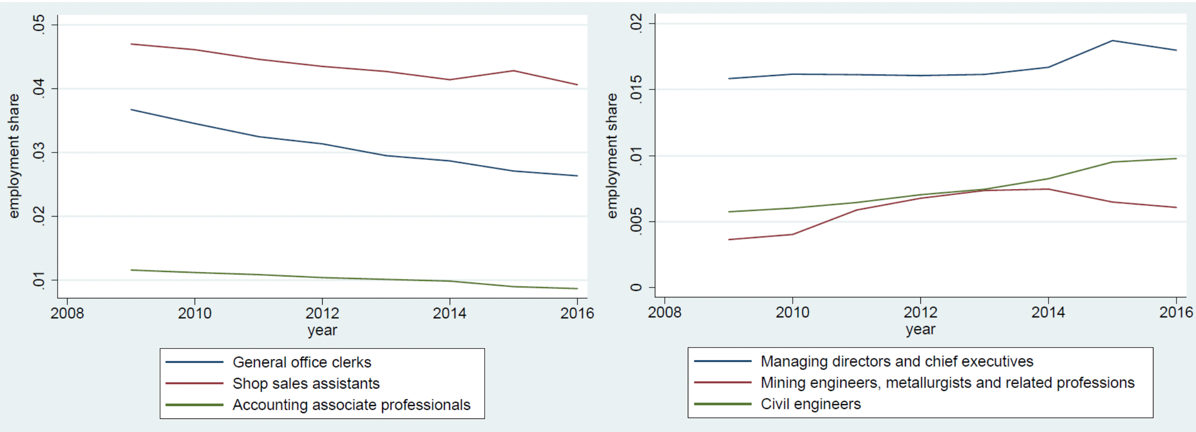
2) $intgrowth = ln \frac{int16}{int09}$

The first variable, *diffint*, is the difference between private broadband subscriptions in 2016 and 2009. I divide this by 100, making *diffint* a number between 0 and 1. The second variable, *intgrowth*, is defined in the same manner as the dependent variable; I take the log of the ratio of private broadband subscriptions in 2016 and 2009. As with R&D expenditures, I'm interest to see if Internet offsets or reinforces the relationship between automation and change in the occupational employment. To examine this, I construct interaction variables *autoprob x diffint* and *autoprob x intgrowth*.

4 Norwegian labour market and automation probabilities

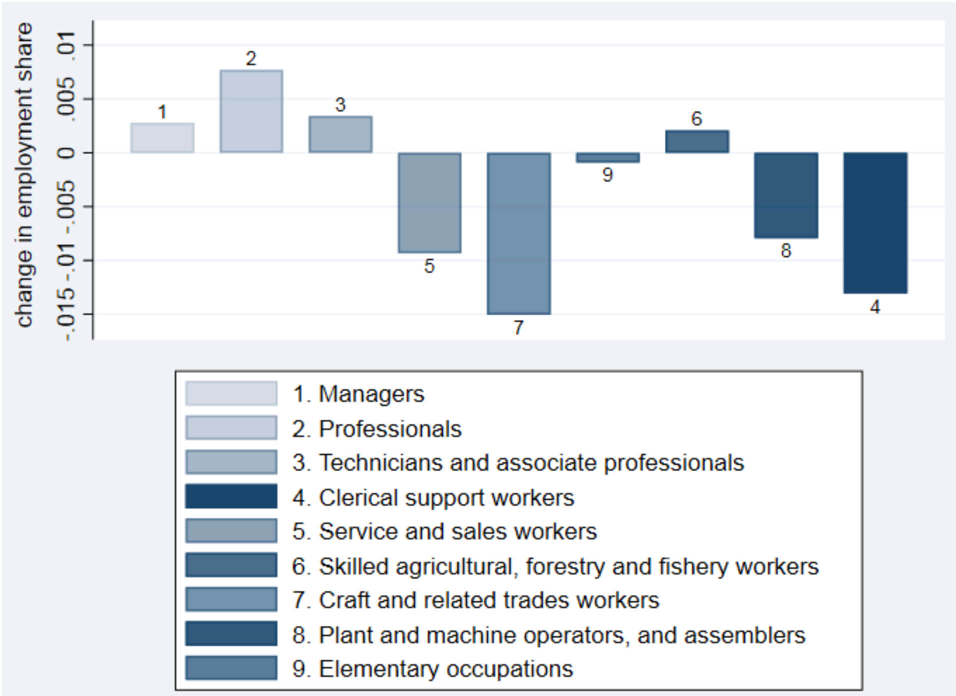
4.1 Occupations

Figure 3: Change in employment share for three risky occupations and three safe occupations.



In Figure 3, I consider the least exposed occupations that have experienced the biggest increase in employment share, and the most exposed occupations that have faced the biggest decline in employment share from 2009 to 2016. The first group has automation probabilities below 0.1, while the second group has automation probabilities bigger or equal to 0.95. In the figure to the left, showing risky occupations, we can see that all jobs have downward sloping curves, indicating that the employment share has decreased from 2009 to 2016. We see the opposite picture in the figure to the right. All of the safe occupations have had a quite steady increase in the employment share. The figures show that high probabilities are associated with decreasing employment, while low probabilities are related to increasing employment. Thus, automation probabilities seem to point out which occupations might be rendered obsolete and which occupations could increase in the future.

Figure 4: Change in employment share in the main occupation groups, sorted by the automation probabilities from left to right.



The impact of automation on the employment is visible in Norway. In Figure 4, the 348 jobs are sorted into 9 occupation groups. They are sorted by the likelihood of being automated, with the lowest likelihood on the left-hand side and the highest on the right-hand side. On average, jobs with a low risk of being replaced by automation have had a positive change in employment share, while jobs with a high risk have had a negative change in the employment share. According to the graph, the safest occupation group is managers, which has experienced a positive employment growth. The average automation probability for this group is 0.12. Second safest group is professionals, and this group has had the largest growth over the last seven years. The riskiest occupation group is clerical support workers, an occupation group which has experienced decreasing employment. The average automation probability for this group is as high as 0.71.

Figure 4 only shows the average decrease or increase in the employment within an occupation group. There are both safe and risky occupations in every group, and it is thus interesting to see which occupations might be causing the patterns observed in Figure 4. In Table 7, considering the safest occupation groups 1 and 2, and the riskiest occupation groups 8 and 4, I list the three biggest[7] jobs within each group. As has been mentioned repeatedly in the

[7] The biggest jobs are defined as the occupations with the highest number of workers in 2016.

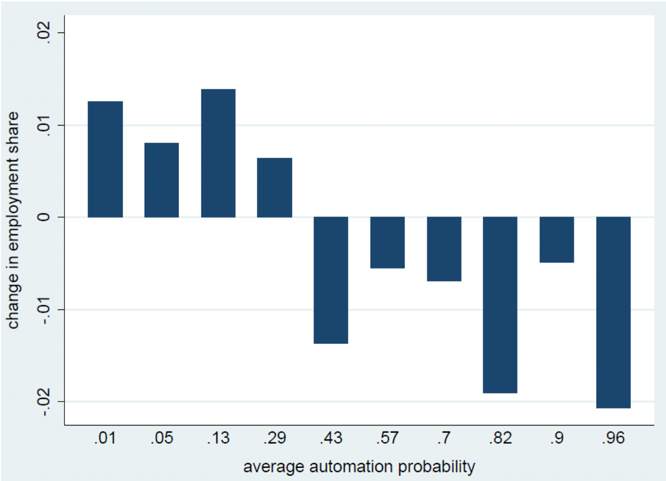
literature, jobs within management, education and health are for now safe from automation. They have low automation probabilities, and either positive or relatively small negative change in employment share. At the same time, office and machine operator jobs are very exposed to automation, something that is already seen in the data.

Table 7: Biggest occupations within the two safest and riskiest groups.

Occupation group	Occupation	Automation probability	Number of workers in 2016	Change in employment share 2009-2016 (%)
1. Managers	Managing directors and chief executives	0.087	35504	0.22
	Retail and wholesale managers	0.16	27489	-0.06
	Business services and administration managers not elsewhere classified	0.355	21671	0.39
2. Professionals	Primary school teachers	0.087	70498	-0.28
	Early childhood educators	0.079	29377	0.07
	Nursing professionals	0.009	25872	-0.12
4. Clerical support workers	General office clerks	0.97	52043	-1.04
	Stock clerks	0.857	30273	-0.23
	Accounting and bookkeeping clerks	0.97	17168	-0.29
8. Plant and machine operators, and assemblers	Heavy truck and lorry drivers	0.41	22652	-0.09
	Food and related products machine operators	0.816	19853	-0.10
	Earthmoving and related plant operators	0.892	18235	-0.08

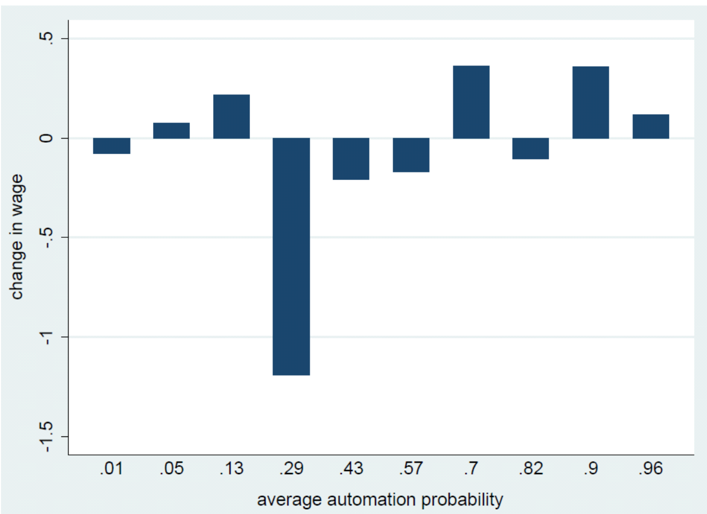
4.2 Employment share, wage and automation probabilities

Figure 5: Relationship between the change in employment share and automation probabilities.



Both in Figure 5 and Figure 6, occupations are divided into 10 equally large groups, and the average automation probability for every group is reported on the horizontal axis. Figure 5 shows that a positive change in employment share is associated with lower probability of automation, while a negative change in employment share is associated with higher probability of automation. There is thus a negative correlation between automation and employment share. This indicates that the probabilities constructed by Frey and Osborne (2017) are consistent with the prediction that new technologies substitute high-risk occupations, while they complement low-risk occupations.

Figure 6: Relationship between the change in wage and automation probabilities.



I find no clear pattern when looking at the automation probability and change in wage.[8] I consider monthly wages, and divide them by yearly basic amount in the National Insurance scheme "G" to make them comparable between 2009 and 2016. Acemoglu and Restrepo (2017) find that automation is associated with wage decrease in the US. This does not seem to be the case for Norway. We might have expected the change in the wage to be negatively associated with automation probabilities, but instead there is a small indication of an increase in the wage for high-risk occupations. An explanation might be that higher wages in these jobs reflect the fact that only high-skilled workers are left in these occupations.

4.3 Job polarization

Several authors have argued that technological unemployment has led to more polarized labour markets in many countries. Studies for the United States (Autor et al., 2006; 2008) and the United Kingdom (Goos and Manning, 2007) have shown that there is employment growth in both the high-wage and low-wage occupations, while there is declining employment in the middle-wage occupations. Furthermore, Goos et al. (2014) find evidence of job polarization in 16 EU countries, in the time period 1993-2010. Norway is included in their study, and they document that Norway has experienced a positive increase in employment shares in low- and high-wage occupations, and a big negative change in the middle-wage occupations. Also OECD (2017) finds that between 1995 and 2015, Northern Europe, containing Denmark, Finland, Norway and Sweden, have experienced a process of polarization away from middle-skill jobs to low- and high-skill employment. It is thus interesting to look if the data I'm using can show evidence of job polarization in Norway in the time period 2009-2016.

By using the same approach as Goos et al. (2014), I divide jobs into low-, middle- and high-wage occupations and look at the change in employment shares. I use data on the average monthly wages in 348 occupations in 2016. In my data set, low-wage occupations range from 23 575 NOK to 37 094 NOK, middle-wage occupations range from 37 198 NOK to 47 479 NOK, and high-wage occupations range from 47 490 NOK to 100 500 NOK. The lowest paid job on average turns out to be survey and market research interviewers, and the highest paid job on average, according to my data, is mining managers.

[8] The large drop observed around 0.3 automation probability in Figure 6 is due to the wage cut for trade brokers, athletes and mining managers.

Figure 7: Occupational shares in low-, middle- and high-wage occupations in 2009 and 2016.

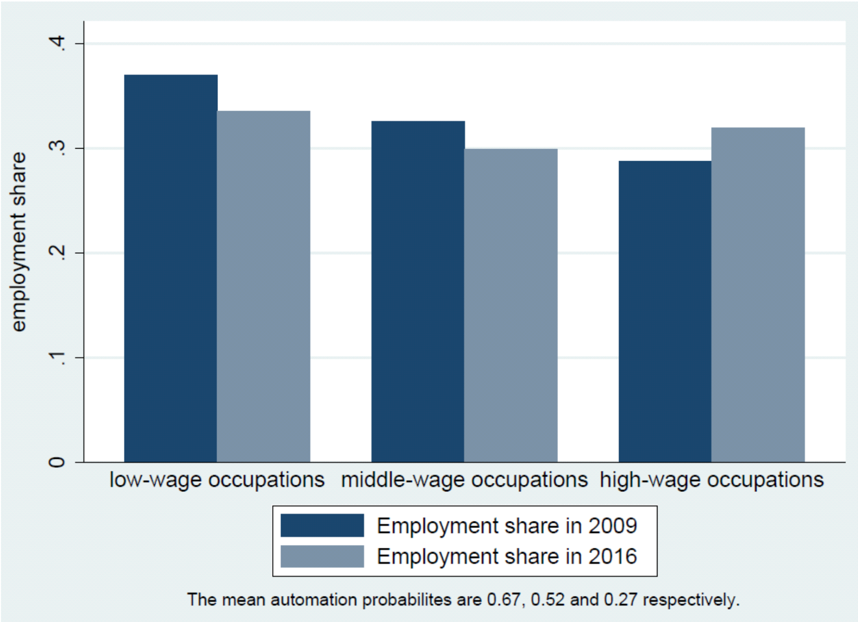


Figure 7 shows that the employment share has decreased in the low- and middle-wage occupations, and increased in the high-wage occupations. This indicates that demand is shifting in favour of more educated workers, known as skill-biased technological change (SBTC). This is in contrast with other studies, which find that the change in employment share is positive for low- and high-wage occupations and negative for middle-wage occupations. According to these studies, the technology is replacing labour in routine tasks, known as routine-biased technological change (RBTC). This change has also been found for Norway, but as pointed out in Autor (2014), employment polarization cannot continue indefinitely. He agrees that many middle-skill tasks are susceptible to automation, but he also argues that many middle-skill jobs demand a mixture of tasks from across the skill spectrum. According to him, many of the middle-wage jobs will stop declining in the future.

RBTC has been the driving force behind declining employment share in the middle-wage occupations in many countries. These occupations have typically been manufacturing jobs, and they are characterized by routine tasks. These tasks can be executed following a precise set of instructions and have therefore been easier to automate. The change in the middle-wage occupations in Norway is relatively small because Norway has less manufacturing jobs than other countries. In addition, education, human health and social work are big industries that also belong to the middle-wage group. These types of jobs are for now hard to automate.

Another interesting result in Figure 7 is that low-wage occupations have the highest automation probability. While there was no correlation between wage change and automation probabilities, there is a relationship between automation probabilities and the wage level. Low- wage occupations are associated with high automation risk, 0.67 in my data, while high-wage occupations are associated with average automation risk of 0.27. This is in line with the model in Frey and Osborne (2017), which predicts that computerisation will mainly substitute for low-skill and low-wage jobs in the near future.

5 Results

In this chapter, I use a log-linear regression equation to look at the relationship between automation and the change in employment within occupations in Norway. My main regression equation is:

$$empgrowth_i = \alpha + \beta autoprob_i + \varepsilon_{i,}$$

where *empgrowth* is the occupational employment growth defined as $ln\frac{number\ of\ employees\ in\ occupation\ i\ in\ 2016}{number\ of\ employees\ in\ occupation\ i\ in\ 2009}$, *autoprob* is automation probabilities constructed by Frey and Osborne (2017) and i stands for occupation.

Table 8: Regression between occupational employment growth and automation probabilities.

	(1) empgrowth	(2) empgrowth
autoprob	-0.413***	-0.317***
	(0.0934)	(0.0408)
constant	0.342***	0.198***
	(0.0511)	(0.0247)
Observations	348	348
R-squared	0.057	0.187

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Regression (2) is weighted by occupations in 2009.

Table 8 shows that there is a negative relationship between automation and occupational employment growth. This means that a higher automation probability in an occupation is associated with decreasing number of employees in the same occupation. This correlation is highly significant, indicating that there is some truth to the constructed probabilities. The difference between column (1) and column (2) is that the second regression is weighted by the occupation sizes in 2009. The number of employees in each job varies greatly, and by giving the bigger jobs more weight, we get more precise estimates. For this reason, I have chosen to weight all the following regressions in the same manner.

Although no causal inference can be drawn, it is still interesting to look at the interpretation of the coefficient. Since automation probabilities are defined between 0 and 1, it does not make sense to talk about a unit increase in *autoprob*. Instead, I will focus on an increase of 0.1

units. The coefficient of 0.32 tells us that an increase of 0.1 units in automation probability, for example from 0.3 to 0.4, is associated with a 3.2% higher decrease in employment. For automation probabilities to increase, one has to overcome certain technology bottlenecks (Frey and Osborne, 2017). Thus, in the short run, automation probabilities are unlikely to change. Therefore, it is more convenient to interpret this coefficient as the difference in the employment growth between two occupations with different automation probabilities. A better interpretation is thus that an occupation with *autoprob* = 0.4 is associated with an employment decrease which is approximately 3.2% higher than an occupation with *autoprob* = 0.3 is associated with.

It is also interesting to look at the interpretation of the constant term. We can see that it is positive, suggesting that an occupation with automation probability equal to zero, faces a positive change in occupational employment. It is not possible to quantify this effect since the constant term captures both the population and employment increase. According to Statistics Norway, the population was 4 799 252 in 2009 and 5 213 985 in 2016. This increase is smaller than the constant term, and we can therefore state that the constant also accounts for an increasing employment in low-risk occupations. This result supports the hypothesis that we are facing restructuring rather than a jobless future.

5.1 Gender

Women are highly represented in occupations such as health care assistants, shop sales assistants, general office clerks and primary school teachers. Health care assistants and primary school teachers are classified as low-risk occupations because their automation probability is lower than 0.5. Shop sales assistants and office clerks are on the other hand classified as high-risk occupations, having an automation probability very close to 1. Men are highly represented in occupations such as carpenters and joiners, commercial sales representatives, shop sales assistants and stock clerks. Only commercial sales representative, having an automation probability of 0.392, is regarded as a safe occupation of these. Since both women and men are employed in safe and risky occupations, it is interesting to see which gender group is more exposed to automation.

Figure 8: Share of women and men in safe and risky occupations.

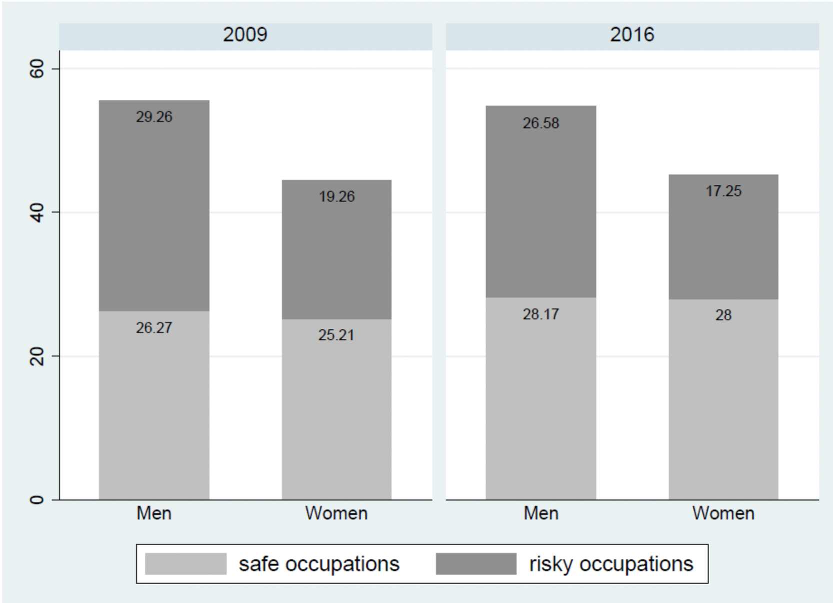


Figure 8 shows the share of women and men when occupations are divided into two groups. One group consists of occupations where automation probabilities are lower than 0.5, called safe occupations. The other group consists of occupations where automation probabilities are higher than 0.5, called risky occupations. We see that in both 2009 and 2016, the share of men and women was approximately the same in the safe occupations. In the risky jobs, the share of men was considerably higher. This is due to the male workers being typically over-represented in highly automatable sectors such as transportation, manufacturing and construction, while female workers are typically over-represented in the health and education sectors that have relatively low automation probabilities. Another interesting observation in Figure 8 is that the share in high risk group has declined for both men and women, while the share in low risk group has increased for both genders. This can be explained by a decrease in the highly automated jobs, moving workers from the risky to more safe jobs.

Table 9: Regression between occupational employment growth for men and women and automation probabilities.

	(1) empgrowth men	(2) empgrowth women
autoprob	-0.269***	-0.360***
	(0.0589)	(0.0411)
constant	0.158***	0.232***
	(0.0352)	(0.0272)
Observations	347	345
R-squared	0.111	0.254

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

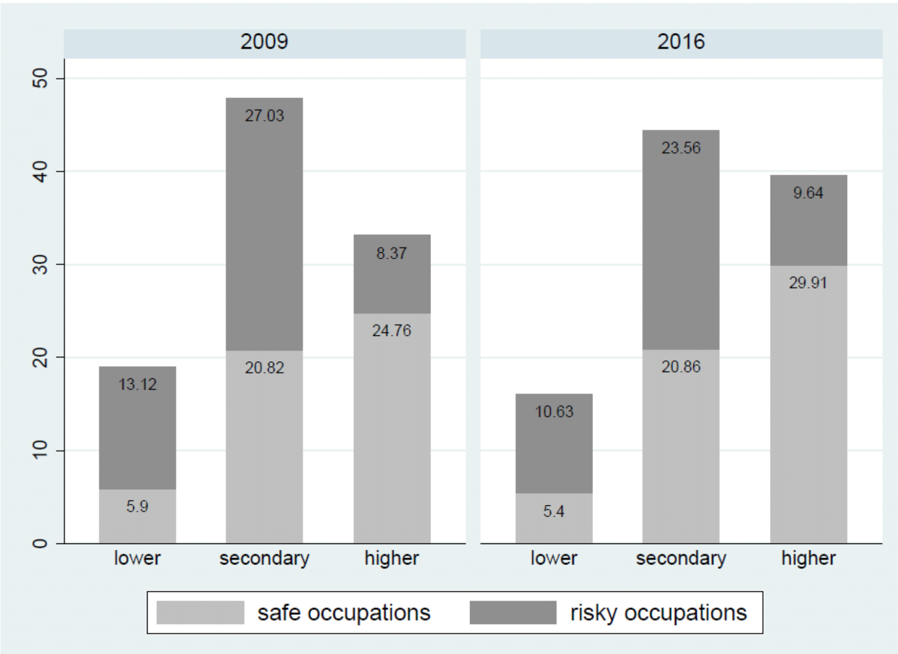
In Table 9, the regression equation above is first estimated on men, then on women. We can see that the coefficient is higher for women, telling us that a difference in automation probabilities of 0.1 is associated with a higher decrease in occupational employment for women than for men. There is no clear-cut answer for why this is the case. One reason might be that women are more mobile between occupations. If the threat of automation within one occupation increases, women might change job, and they might do it quicker than men. Another explanation might be that women are more hurt by an increase in automation, at least for now. This might seem odd taking into account that the share of men in highly automatable occupations is higher. But, by looking at what type of jobs have faced the biggest decline lately, one can observe that women account for a big share of employees in these occupations.

Although men face a higher risk of automation in total, women seem to be more exposed at the moment. As could be seen from Figure 4, general office clerks and accounting associate professionals are two of three high-risk occupations in Norway that have decreased the most in the period 2009 – 2016. A large share of women is employed in these occupations, and also in other jobs related to administration and finance. The higher correlation between automation and occupational employment for women can be explained by these occupations having a high automation probability, and at the same time facing the largest employment decrease in the recent years.

5.2 Education

Highly educated people are mostly present in occupations such as primary school teachers, nursing professionals, secondary education teachers and early childhood educators. All of these occupations have an automation probability lower than 0.1. Lower educated people are represented in occupations such as shop sales assistants, cleaners and helpers in offices, hotels and other establishments, child care workers and stock clerks. Only child care worker is regarded as safe of these occupations. We can see that there is a tendency for high educated people to be less exposed to the automation risk, while people with less education work exactly in the jobs that might disappear in the future.

Figure 9: Share of individuals with lower, secondary and higher education in safe and risky occupations.



As with gender, I sort individuals based on their education into safe and risky occupations, where safe occupations have automation probabilities below 0.5, and risky occupations have automation probabilities above 0.5. As we can see from Figure 9, the shares are quite similar in 2009 and 2016. In both years, individuals with lower education are highly represented in risky occupations, while individuals with higher education are mostly present in safe occupations. The share of individuals with higher education have increased the past years, making the share of higher educated people to increase in both safe and risky jobs. We can also observe that the share of individuals with lower and secondary education in safe occupations has stayed the same, while it has decreased in risky occupations.

Table 10: Regression between occupational employment for individuals with different education levels and automation probabilities.

	(1) empgrowth lower	(2) empgrowth secondary	(3) empgrowth higher
autoprob	-0.213***	-0.288***	-0.0411
	(0.0756)	(0.0515)	(0.0523)
constant	0.00832	0.133***	0.234***
	(0.0467)	(0.0320)	(0.0306)
Observations	346	344	343
R-squared	0.055	0.131	0.003

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

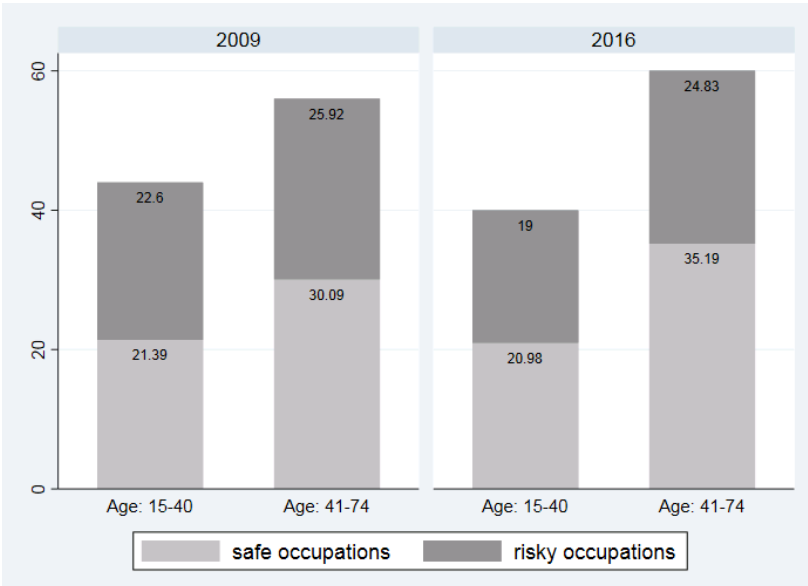
From Table 10, we can see that the correlation between automation probabilities and occupational employment is higher for individuals who have secondary education. As with gender, there is no clear-cut answer for why this is the case. But the result can again be explained based on which occupations have experienced the largest employment decrease in the recent years. From the literature it is known that individuals with secondary education typically have jobs involving simple computational and repeatable tasks (Autor et al., 2003; Goos et al., 2009; Autor and Dorn, 2013). Since these types of jobs are being automated now, individuals with secondary education face the largest decrease in the occupational employment.

Also for low educated individuals, there is a significant and negative relationship between automation probabilities and occupational employment. This means that jobs with lower-educated employees are also disappearing, but to a lesser extent than routine jobs, at least for now. After some years, when automation hits transportation and construction sector to a bigger extent, low-educated people could be at higher risk. A large share of employees in these types of occupations is men, and it might thus seem that low-educated men will face the biggest threat in the future. Furthermore, we see that the relationship between automation and occupational employment is non-significant for high-educated employees. This reflects the greater adaptability of more highly educated workers to technological changes and the fact that they are employed in jobs consisting of tasks which are still hard to automate.

It is also interesting to look at the constant term. It is very low for low-educated people, and quite high for highly-educated employees. This result suggests that employment has not increased in the low-skilled jobs. Rather, it has been declining. At the same time, high-skilled jobs have had an increasing employment. While technology seems to only have labour-saving effect in the low-skilled jobs, it points to more labour-augmenting effect in the high-skilled jobs. The results indicate that it might be an advantage to have higher education in the coming years.

5.3 Age

Figure 10: Share of younger and older individuals in safe and risky occupations.



There is no sharp distinction in where the younger or older people work, suggesting that most of the occupations employ both young and old individuals. There are, however, differences in the shares of younger and older individuals in the safe and risky occupations. By looking at Figure 10, we can see that individuals in the age group 15-40 are almost evenly distributed between risky and safe occupations. Individuals in the age group 41-74 are on the other hand more highly represented in the safe occupations. This share was 30.1% in 2009, and it increased to 35.2% in 2016. We can also observe that the shares of younger and older in risky occupations have decreased from 2009 to 2016.

Following the same procedure as for gender and education levels, I estimate the relationship between automation probabilities and occupational growth for three different age groups.

Column (1) and (2), in Table 11, show that this relationship is quite similar between younger and older individuals. Age does therefore not seem to be an important factor when analysing the threat of automation. The correlation is however somewhat higher for the individuals in the age group 41-74. This might be due to older people finding it relatively hard to adapt and retrain than younger cohorts.

Table 11: Regression between occupational employment for individuals in different age groups and automation probabilities.

	(1) empgrowth Age: 15-40	(2) empgrowth Age: 41-74	(3) empgrowth Age: 25-55
autoprob	-0.273***	-0.328***	-0.321***
	(0.0590)	(0.0473)	(0.0427)
constant	0.0775***	0.266***	0.178***
	(0.0293)	(0.0304)	(0.0243)
Observations	347	348	348
R-squared	0.109	0.191	0.187

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Column (3) considers age group 25-55. It might be that the youngest individuals are mostly employed in highly automatable jobs due to not having higher education. Also, some of the young employees might be temporary in the labour market, before they return back to school. This choice might be correlated with automation probabilities. It might also be that the oldest employees leave labour market earlier since they might lack the skills needed to adapt to new technologies. To exclude these factors from impacting my results, I choose to restrict sample to the individuals in the age group 25-55. From Table 11, we can see that the correlation between automation probabilities and occupational employment stays the same, showing that above-mentioned factors do not impact my results.

6 Other possible factors

The relationship between automation probabilities and occupational employment might be spurious due to the presence of a certain third, unseen factor. The financial crisis, oil price drop and globalisation might be correlated with automation, and hence drive my results. In this chapter, I will argue why none of these factors seem to do that.

6.1 Financial crisis

The financial crisis in 2008 is said to have the worst global downturn since the Second World War, leading to millions of job losses and deterioration in working conditions. This crisis also hit Norway, but the harmful impacts were quite modest. Norway experienced an annual stagnation of about one percent and substantially lower unemployment rates than almost any comparable economies, with a little more than three percent unemployment in 2009 (Grytten and Hunnes, 2010). An article by Doppelhofer and Thøgersen (2014), also states that Norway was one of the countries which was least affected by the crisis. They argue that this was partly due to our petroleum and commodity-based business structure, and partly because of a well-matched monetary and fiscal policy. My main concern is that impacts from financial crisis, such as loss of many jobs, might matter for my analysis. However, since my analysis starts in the year 2009, and financial crisis didn't harm labour market in Norway to a large extent, this factor should not impact my results.

6.2 Oil price drop

The oil price drop in 2014 might matter for my study since Norway is dependent on petroleum for income, exports and jobs. Oil and gas extraction and pipeline transport represented about 21% of Norway's GDP in 2013 (Cappelen et al, 2014). When it comes to employment, a report from Statistics of Norway has suggested that approximately 9% of Norwegian jobs were directly or indirectly related to petroleum activities in 2013 (Statistics Norway, 2016). Based on their input-output calculation, they also estimated that the employment related to the petroleum industry decreased from 230 000 in 2013 to 205 000 in 2015. Since this decrease is exactly in my period of interest, oil price drop might be the reason for the negative relationship between automation and the change in the employment observed in my data.

Table 12: Regression between occupational employment and automation probabilities excluding oil workers.

	(1) empgrowth	(2) empgrowth
autoprob	-0.317***	-0.329***
	(0.0408)	(0.0412)
constant	0.198***	0.196***
	(0.0247)	(0.0245)
Observations	348	348
R-squared	0.187	0.185

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Baseline regression in column (1). Regression (2) excludes workers directly linked to oil and gas.

The oil price drop that took place in 2014 led to a decrease in employment in certain occupations, something that could be the driving force behind the negative correlation between automation and employment. Due to this, I drop all employees related to extraction and production of crude oil and natural gas[9]. Table 12 column (2) shows the correlation between *autoprob* and *empgrowth* on the remaining occupations. We can see that the strong relationship between automation and employment has remained, and I can thus conclude that oil price drop is not driving my results.

6.3 Globalisation

Challenges related to globalisation, especially offshoring and exposure to imports from China, and declining employment have also been widely discussed. Findings in the literature suggest that offshoring has no effect or a slightly positive effect on sectoral employment (Hijzen and Swaim, 2007; Wright, 2013). Hence, productivity gains from offshoring seem to be sufficiently large such that the jobs created by higher sales completely offset the jobs lost by relocating certain production stages to foreign production sites. However, the displacement effect of offshoring might be correlated with automation, and impacting my results. Blinder (2009) defines two characteristics of jobs that can be offshored. The first is that the job does not have to be performed at a specific work location. The second is that the job does not require face-to-face contact. Take for example contact centre salespersons. This occupation

[9] Using Standard Industrial Classification, I eliminate employees directly linked to oil, which have a Nace Rev.2 industry codes starting on 06 and 091.

has an automation probability of 0.99. At the same time, this occupation can be offshored since it can be done from whatever work location and does not require face-to-face contact. An opposing example is receptionists. This occupation has an automation probability of 0.96, and is thus highly automatable. But a work of receptionist must be performed at specific location and requires face-to-face interaction. Thus, it seems that it is easier to expose an occupation for technology than for offshoring. Although more occupations are threatened by robots, I still want to assess empirically that offshoring is not impacting my results. Therefore, I choose to exclude occupation group 4, clerical support workers, and 8, plant and machine operators, and assemblers. These groups are chosen since Blinder (2009) defines machine operators and clerical workers as the most offshorable occupations.

Exposure to imports from China has been investigated in Norway. When using data for the period 1996-2007, Balsvik et al. (2015) found a negative impact of exposure to competition from China on the manufacturing employment share in the Norwegian local labour market. To eliminate this factor as the driving force behind my results, I choose to exclude all employees in the manufacturing jobs[10].

Table 13: Regression between occupational employment and automation probabilities excluding possible offshorable jobs and manufacturing workers.

	(1) empgrowth	(2) empgrowth	(3) empgrowth
autoprob	-0.317***	-0.303***	-0.264***
	(0.0408)	(0.0482)	(0.0404)
constant	0.198***	0.197***	0.209***
	(0.0247)	(0.0254)	(0.0259)
Observations	348	290	348
R-squared	0.187	0.160	0.142

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Baseline regression in column (1). Regression (2) excludes occupation group 4, clerical support workers, and 8, plant and machine operators, and assemblers. Regression (3) excludes manufacturing workers.

[10] Using Standard Industrial Classification, I eliminate manufacturing employees, which have a Nace Rev.2 industry codes 10-33.

Table 13 shows the relationship between automation and occupational employment when occupation groups 4 and 8 are excluded (column 2) and when manufacturing employees are excluded (column 3). The change in coefficient is quite modest in column (2), showing that the predictive power of the probabilities remains significant, even when excluding the most automatable occupation groups. The coefficient in column (3) drops to 0.26. This results is somewhat expected. Employees in manufacturing jobs were exposed to automation quite early, and the predictive power of automation probabilities should be relatively high for this group. Although the coefficient drops, the relationship is still significant, indicating that the declining employment share in my analysis is related to automation. Thus, either offshoring or imports from China seems to have an impact on my results.

7 R&D and Internet

Studies that try to understand the effect of technological advances on employment have used various proxies for technology, where R&D expenditures and broadband access have been common measures. As mentioned in chapter 2, literature agrees on the impacts from these two technologies. Higher R&D expenditures are consistent with higher employment, especially in high-tech firms. More Internet leads also to higher employment, but only in the high-skilled occupations. These studies look at the total employment, while I only consider occupational employment, and thus only direct effect of these technologies. The purpose of this chapter is to analyse whether R&D expenditures and Internet subscriptions are mitigating or magnifying the negative relationship between automation probabilities and the change in the occupational employment.

By interacting automation probabilities with first R&D expenditures, and then Internet subscriptions, I want to analyse if the sign and magnitude on occupational employment growth changes. A negative coefficient would imply that more R&D or broadband in risky occupations is associated with negative employment growth. However, if R&D or broadband has an offsetting effect on the correlation between automation and employment, we should expect a positive sign. In the case of R&D expenditures, I use county-level fixed effects to estimate the relationship between interaction variables and occupational employment growth. The regression equation used is:

$$empgrowth_i = \alpha + \beta_1 autoprob_i + \gamma_1 autoprob_i \; x \; rd_1 + \ldots + \gamma_c autoprob_i \; x \; rd_c + \varepsilon_{i,}$$

where *rd* is either *diffrd* or *rdgrowth* and c stands for county. In the case of Internet subscriptions, I use municipality-level fixed effects, and the regression equation becomes:

$$empgrowth_i = \alpha + \beta_1 autoprob_i + \gamma_1 autoprob_i \; x \; int_1 + \ldots + \gamma_m autoprob_i \; x \; int_m + \varepsilon_{i,}$$

where *int* is either *diffint* or *intgrowth* and m stands for municipality.

Table 14: Regressions including R&D expenditures and private Internet subscriptions.

	(1) empgrowth	(2) empgrowth	(3) empgrowth	(4) empgrowth
autoprob	-0.204***	-0.201***	-0.235***	-0.226***
	(0.0222)	(0.0193)	(0.0210)	(0.0208)
autoprob x diffrd	0.0213			
	(0.0160)			
autoprob x rdgrowth		0.0377		
		(0.0260)		
autoprob x diffint			0.186*	
			(0.110)	
autoprob x intgrowth				0.0944
				(0.0824)
constant	0.214***	0.214***	0.161***	0.161***
	(0.00629)	(0.00713)	(0.00559)	(0.00575)
Observations	5,932	5,932	47,506	47,506
R-squared	0.058	0.058	0.075	0.075

Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

The direct effect of new technologies is the labour-saving effect. One might thus believe that R&D expenditures and Internet, interacted with automation probabilities, would give an even more negative relationship with occupational employment growth. My results, represented in Table 14, show the opposite. Occupations which have a high automation probability and high R&D expenditures or broadband access are not correlated with employment. The sign even changes, and becomes positive, showing that more R&D or Internet is associated with positive employment change in the risky occupations. Only one of the coefficients is significant at 10% level, so these results should be interpreted with caution.

Although it is difficult to give a quantitative interpretation of the interaction variables, it is possible to say something about the direction of the effect. If we increase both the automation probability and R&D expenditures or broadband subscriptions, we should expect a non-negative or even positive relationship with occupational employment growth. This indicates that employment in occupations with high automation probability will not be harmed by new technology in the form of higher R&D or broadband access. An explanation might be that occupations having a high probability might be those having already a lot of machines. If the technology possibilities are used up, new technology might not have the same strong labour-saving effect anymore.

8 Discussion and conclusion

The threat of automation is a controversial issue. Some argue that we have nothing to be afraid of. Others claim that this time is totally different from others, and we will soon face a massive unemployment caused by robots taking over increasing number of tasks performed by humans. We have witnessed how robots beat humans in quizzes, how cashiers are replaced by machines and how a car can drive without a driver. These are some of the technological advances that have happened, and almost no one could foresee them coming. Several experts have tried to predict what will happen next, but technological advances are developing at a speed that very few can follow. One of the most remarkable studies trying to predict what will happen in the future is by Frey and Osborne (2013). This paper was the first one trying to put a number on how many jobs were at risk of being replaced by technology and found that 47% of the jobs in the US were facing a high risk of automation. Since the study by Frey and Osborne got a noticeable amount of attention, many adapted their probabilities to occupations in other countries, and found a worrying number of jobs being in the high-risk category. Pajarinen et al. (2014) did it for Norway, and they found that 33% of jobs could disappear within the next two decades. Many of these studies have only estimated how many jobs are at risk, but very few have looked at how these probabilities relate to actual labour market changes. This thesis is one of the first studies that measure the relationship between the automation probabilities constructed by Frey and Osborne (2013) and employment change within occupations. It provides an empirical basis for the ongoing debate on how the technological advances should be met.

In this thesis, I have tried to assess the relationship between automation and occupational employment in Norway. I have looked at 348 Norwegian occupations, and used automation probabilities constructed by Frey and Osborne (2013) as proxy variables for the technological advances. My results suggest that there is a negative and significant correlation between automation and employment change within an occupation. Occupations with high automation probabilities are associated with declining employment in the period 2009-2016. The correlation is approximately -0.32, indicating that in the absence of technology bottlenecks, an increase in automation probability of 0.1 units in one occupation is associated with 3.2% higher decrease in the employment in the same occupation. This relationship is at the moment strongest for women and individuals with secondary education. Age does not seem to have any impact on the magnitude of the threat of automation. In the long run, however, men and low-educated employees seem to face a bigger threat of automation since they are highly represented in risky occupations.

There could be other factors, correlated with automation probabilities, driving my results. By changing my dataset in different ways, I argue why either financial crisis, oil price drop, or globalisation seems to impact my results. When looking at two other technology measures, R&D expenditures and private broadband subscriptions, I find that they mitigate the negative relationship between automation and occupational employment. This does not mean that one should invest more in R&D or increase Internet use to cope with technological unemployment. However, this indicates that either R&D or Internet seems to be directly harmful in occupations with high automation probabilities. Assuming that these occupations are the ones with already a lot of technology, points to the fact that R&D and Internet have a more labour-augmenting than labour-replacing effect in risky jobs.

Combination of declining costs of technologies and ongoing advances in computing, artificial intelligence, and robotics, has raised concerns about automation leading to significant job losses and worsening income inequality. Politicians are actively debating on how to deal with this, and basic income and robot tax have been suggested as potential responses to automation. An universal basic income could provide a more secure and substantial safety net for all people, and achieve the goal of more equality, while a robot tax could raise government revenue and slow down automation. Abbott and Bogenschneider (forthcoming 2018) point out that higher unemployment due to automation will lead to government losing a substantial amount of tax revenues, and they argue that today´s tax policy will have to be redesigned. The appealing feature with a robot tax is that the money from this tax could be used to retrain workers and to expand education and health care sector, and thus provide lots of hard-to-automate jobs.

My results favour the hypothesis that we are facing restructuring rather than a jobless future. The positive constant term, found in almost all regressions, reflects the fact that occupations with low risk of being automated face an employment increase. There is also evidence that low-skilled occupations are mainly decreasing, while high-skilled occupations seem to enjoy an influx of employees. The likely challenge for the coming years lies in coping with rising inequality and ensuring sufficient retraining, especially for low- skilled workers.

This thesis has assumed that probabilities constructed by Frey and Osborne are good proxy variables for technological advances. It should be noted that they are partly subjective, and should therefore be used with caution. My analysis shows that these probabilities are correlated with the change in occupational employment, indicating that Frey and Osborne´s predictions can be used to get an idea of which occupations will be automated first. Compared to other countries, Norway has fewer manufacturing and private sector jobs, but this does not make it safe from automation. New technology is also replacing workers in occupations such as accounting and bookkeeping professionals, shop sales assistants and general office clerks, and we have seen that these occupations have been facing a declining employment from 2009 to 2016. It is thus vital to understand that also Norway has been exposed to automation and will most likely continue to see workers being replaced by upcoming technological advances. The robots are already here. We just have to make sure that workers are able to race with them, and not against them.

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