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Will Robots Replace Us?

An Empirical Analysis of the Impacts of Robotization on Employment in the Norwegian Manufacturing Industry

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[1]Parts of the data used in this thesis are obtained from the Norwegian Labor Force Survey (AKU). Anonymized data are made available by the Norwegian Centre for Research Data (NSD). The data was originally collected and facilitated by Statistics Norway (SSB). Neither Statistics Norway nor NSD are responsible for the analyses or interpretation of the data presented here.

Abstract

Rapid advances in robotics, artificial intelligence, and digital technologies have introduced renewed concern that labor will become redundant. The aim of this thesis is to assess whether there exists a relationship between robotization and employment in the time periods 1996-2005 and 2008-2015 in Norwegian manufacturing industries. We exploit data on operational robots from the International Federation of Robotics and individual level data from the Norwegian Labour Force Survey, to assess a potential relationship between increased robotization and the probability of being employed within the manufacturing industries. Utilizing linear probability models, we find no negative relationship between increased robotization and the probability of being employed in Norwegian manufacturing industries. Further, we find indications of a relationship between increased robotization and skill-biases. However, the relationships are of no economic significance. Our findings are consistent with previous research on the impacts of robotization on employment outcomes. Further, we find that robotization is distinct and weakly correlated to import density and capital density.

Acronyms

AKU	Norwegian Labour Force Survey
GDP	Gross Domestic Product
IFR	International Federation of Robotics
ISIC	International Standard Industrial Classification of All Economic Activities
IV	Instrumental Variables
LPM	Linear Probability Model
MLE	Maximum Likelihood Estimation
NAV	Norwegian Labour and Welfare Administration
NSD	Norwegian Centre for Research Data
OLS	Ordinary Least Squares
SSB	Statistics Norway

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1 Introduction

Rapid technological advances raise concerns that labor will become redundant (Akst, 2013; Autor, 2015; Brynjolfsson & McAfee, 2014). The world is entering a second machine age, where the importance of technology is of unprecedented magnitude. As recent advances in robotics, artificial intelligence, and digital technologies continue to penetrate the economy, the opportunities for workers to find employment may change. Developments in robot technology have increased the number of tasks eligible for automation, tasks previously performed by human labor. The ability of humans to race against or with the machines will determine the employment effects of the new technologies (Brynjolfsson & McAfee, 2014). The future of work is becoming increasingly uncertain.

The consequences of automation on employment have been a recurring topic over the last two centuries. One of the most well-known examples of workers' opposition against new technology is the Luddites in the 19th century, destroying the new machinery that replaced them. In 1930, John Maynard Keynes popularized the term "technological unemployment", describing the reduction in jobs caused by technological change as a disease humanity would face in the years ahead (Keynes, 1930). Keynes' main concern was that technological unemployment would grow at a faster rate than the rate at which the new technology created new jobs. Wassily Leontief shared Keynes' pessimistic view on the future of employment, drawing an analogy to the redundancy of horse labor in the early 20th century, caused by new technologies. Leontief speculated that "Labor will become less and less important... More and more workers will be replaced by machines. I do not see that new industries can employ everybody who wants a job" (Leontief, 1952). Pessimistic and concerned views on the future of labor have occasionally occurred in the public debate over the past century. However, the realization of former predictions have never been closer, as we stand on the verge of a shift in technology and a new advent of machines ready to take over as the main source of "labor".

Previously, there has been a limited amount of evidences on the effects of increased robotization on employment outcomes. According to Keynes (1930), technological unemployment will reduce the labor demand when automation increases. The infancy of the research field notwithstanding, evidence suggests a negative employment to population effect from increasing the number of robots relative to workers in the United States (Acemoglu & Restrepo, 2017).

Further, evidence shows that robots did not significantly reduce total employment, although the employment shares shifted to the disadvantage of low-skilled workers in the EU (Graetz & Michaels, 2017). Further, to our knowledge, Graetz and Michaels (2017) is the first paper to explicitly analyze the economic contributions of modern industrial robots and their effect on labor market outcomes. However, Autor, Dorn, and Hanson (2013) and Balsvik, Jensen, and Salvanes (2015) suggest that changes in the manufacturing employment in the US and Norway, respectively, can be attributed to increased exposure to import competition from low-cost countries, in particular China.

To the best of our knowledge, Norway has not been subject to research on the effects of increased robotization on employment. We estimate the relationship of industrial robots on the probability of being employed in the Norwegian manufacturing industry using linear probability models. As a measure of the degree of robotization in each industry, we use *robot density*, defined as the number of robots per 1,000 workers. To account for non-linear relationships, endogeneity problems, and a skewed sample, we include a robustness analysis. Our data is constructed by linking data from the International Federation of Robotics on operational industrial robots in Norwegian manufacturing industries to individuals in the Norwegian Labour Force Survey connected to the industries. Based on previous literature, we do not expect an increase in robotization to be associated with a negative impact on the probability of being employed within Norwegian manufacturing industries.

We hope that our thesis will provide a foundation for future research on the effects of increased use of robotics, artificial intelligence, and other digital technologies on labor market outcomes, in particular in a Norwegian context. This thesis will be limited to focus on the relationship between the use of industrial robots and employment outcomes. We recognize that the data we use impose limitations in our analysis, and these limitations will be discussed in Sections 4 and 5.

The results from our linear probability models (LPM), show that there is a positive relationship between increased robotization and employment probability in the period 1996 - 2005. A one unit increase in robot density is associated with a 0.1 percentage point higher probability of being employed. There is no relationship between increased robotization on employment probability in the period 2008 - 2015, however, being skilled is associated with a 0.2 percentage point higher probability of being employed if robot density increases by one unit. We emphasize that a one unit increase in robot density is a substantial increase in a Norwegian context. Over the past 20 years, robot density in the Norwegian manufacturing industry, has remained at a relatively steady level of 0.25 robots per 1,000 workers, and thus, the associated changes in employment probability are of little economic significance. In the 2008 - 2015 period, increased import competition is negatively associated with employment. The robustness analysis do in general not alter the results from the LPM, however, there are indications of skill-biases introduced by increased robotization in the period 1996 - 2005. Practically, the effects are zero, considering how large a one unit increase in robot density is in a Norwegian context.

The remainder of the thesis continues as follows. In Section 2, we present theories and previous research relevant for our thesis, while Section 3 presents our empirical methodology. In Section 4, we present developments in the Norwegian manufacturing industry, background on the robot data utilized, and descriptive analyses of the development of robots. Section 5 presents the data obtained from the Norwegian Labour Force Survey and descriptive statistics for our final sample. In Section 6, we present the results from our main analyses and robustness analyses, while we discuss the results in Section 7, before we conclude in Section 8.

2 Possible Effects of Robots on Labor Market Outcomes

Our thesis investigates whether increased automation of tasks reduces employment, referred to as technological unemployment. We also investigate whether technological changes induced by increased automation of tasks are skill-biased. The theories of technological unemployment and skill-biased technological change are closely related. However, the absence of the former does not necessarily exclude the presence the latter.

2.1 Technological Unemployment and Skill-Biased Technological Change

In 1930, John Maynard Keynes popularized the term "technological unemployment". The term technological unemployment refers to unemployment caused by the introduction of new technology substitutable with human labor. Keynes expressed a pessimistic view on the future of human labor if technological unemployment occurs at a faster rate than the rate at which new technology creates new types of jobs (Keynes, 1930). Following Keynes' concerns, Postel-Vinay (2002) investigates the dynamics of technological unemployment, comparing short-term and long-term effects of technological progress on employment. By applying a simple model of technological progress-based endogenous job destruction, he finds evidence consistent with Keynes' concerns, suggesting negative effects of technological progress on the long-run level of employment. Considering short-run effects, Postel-Vinay finds that faster technological change has a positive and potentially important influence on the level of employment causing a drop in job destruction.

Feldmann (2013) investigates technological unemployment in industrial countries. His paper analyses the impact of technological change on unemployment, using annual data from 21 countries in the period 1985 to 2009. Feldmann uses the ratio of triadic patent families, a set of patents registered in different countries to protect the same invention, to population as a proxy for technological change (OECD, 2016). The results suggest that faster technological change is likely to have a substantial negative effect on employment. However, the effects appear to be short-term, persisting for three years and disappearing in the long-term. Accordingly, the findings suggest the negative effects to be transitory, not permanent.

One of Keynes (1930)'s major concerns, was that technological unemployment would grow at a faster rate than the rate at which new technologies create new jobs. Building on this concern, Brynjolfsson and McAfee (2014) address whether the widening gap in skill level emerging between workers entering and workers exiting employment is due to technological change. As new technology enters the economy, and fundamentally alters demand for labor, technological change may be skill-biased if institutions and people are unable to adjust to the technological progress. Skill-biased technological change is induced by a shift in production technology, causing a shift in the relative demand of skilled versus unskilled labor, and is closely related to technological unemployment. When new technologies cause some types of jobs to become redundant, new types of jobs are created simultaneously. These new jobs tend to require a different and usually higher skill level than those crowded out by the new technology, resulting in a compositional change in the skill level of the labor force. Hence, technological change is biased towards high-skilled labor. Skill-biases are concerning with regard to the impact they have on inequality. A shift towards high-skilled labor is likely to increase the inequality in the society (Brynjolfsson & McAfee, 2014; Violante, 2008).

Berman, Bound, and Griliches (1994) investigate the change in relative skill demand in U.S Manufacturing in the 1980s. They find evidence suggesting that biased technological progress is the main explanation of the shift in demand from unskilled to skilled labor evident in US manufacturing. The bulk upgrading of skill within manufacturing cannot be attributed to trade. The result is striking in the sense that manufacturing is particularly exposed to trade. Thus, skill upgrading in other industries are unlikely to be explained by trade. Further, Berman et al. (1994) emphasize that similar results should be evident in other developed countries, if the increase in the relative demand for skilled labor is attributable to technological change. Building on the evidence found in the United States by Berman et al. (1994), Berman, Bound, and Machin (1998) present strong evidence suggesting that the changes in unemployment occurring in the developed world in the 1980s, can be attributed to skill-biased technological change. By studying ten developed economies using a two-factor, two-good small open economy version of Heckscher-Ohlin theory, they find that shifts in production technology are skill-biased, increasing the equilibrium ratios of skilled versus unskilled labor. Further, Berman et al. (1998) stress that skill-biased technological change is not the sole explanation for the increase in relative demand for skill. Sector-biased technological change and Heckscher-Ohlin trade are likely partial explanations of the changes evident in developed countries.

Berman et al. (1994) and Berman et al. (1998) find evidence suggesting that changes in unemployment in the 1980s, can be attributed to skill-biased technological change. However, the world trade dynamics have subsequently changed dramatically. In the 1990s, China emerged as one of the world's largest manufacturing producers, and Chinese exports to the US increased rapidly (Autor et al., 2013). Hence, the changes in labor market outcomes, that could be attributed to the introduction of new technology causing skill-biases in the 1980s, may from the 1990s be a consequence of increased imports from emerging low-cost countries. Autor et al. (2013) examine the effects of increased Chinese import competition on labor market outcomes in the US from 1990 to 2007. They exploit differences in exposure to trade in different regions to define local labor markets, commuting zones. Commuting zones differ in exposure to import competition due to regional differences in the importance of manufacturing industries. Using an instrumental variables strategy, they create an instrument for US exposure to trade from the exposure to trade in other high-income-countries, and use ten-year-lagged employment levels to exclude the possibility that contemporary employment is affected by anticipated Chinese trade. The results suggest that increased exposure to Chinese imports has large effects on US labor market outcomes. As much as 20 percent of the reduction in the labor market share of manufacturing industries, can be attributed to shocks in Chinese imports to the US between 1990 and 2007.

Similarly, Donoso, Martín, and Minondo (2015) find negative effects of increased Chinese imports on the probability of being employed in the Spanish manufacturing sector, using micro-level data. A standard deviation increase in Chinese import competition increases the probability of becoming unemployed by between 0.8 and 3.5 percentage points, representing between 9 and 44 percent increase relative to the unconditional probability of becoming unemployed. These effects are twice as large as the effects presented by Autor et al. (2013) for the US. The effect of increased exposure to imports from China on employment in the manufacturing industry, has been analyzed for Norway. Based on Autor et al. (2013), Balsvik et al. (2015) find that increased regional exposure to Chinese imports equivalent to 10,000 Norwegian kroner (NOK) per worker, reduces the manufacturing employment share by 0.125 percentage points. Additionally, they find that mainly unskilled workers are negatively affected by the increased exposure to Chinese imports. The findings presented above suggest that increased exposure to trade from low-cost countries, rather than skill-biased technological change, is the main reason for the decline in manufacturing employment in the 1990s and 2000s in high-income countries.

2.2 Effects of Robotization on Employment

Increased robotization is likely to affect employment through mechanisms such as technological unemployment and skill-biased technological change. Acemoglu and Restrepo (2017) estimate the impact of industrial robots on employment and wages in the US between 1990 and 2007. As a measure of the exposure to robots, they use robots per 1,000 workers. Between the early 1990s and the late 2000s, exposure to robots in the U.S increased from 0.4 robots per 1,000 workers to 1.4 robots per 1,000 workers, compared to a change from 0.6 to 2.6 in Europe over the same time period. By applying a model where robots and human labor compete in the production of different tasks, they analyze the effect of the increase in robot usage on local US labor markets. Exploiting differences in exposure between commuting zones, they find that an increase of one robot per 1,000 workers reduces the employment to population ratio by about 0.18-0.34 percentage points. This translates into aggregated effects of between 3 and 6.4 workers losing their jobs, resulting from the introduction of one more robot per 1,000 workers in the national economy. Further, aggregated wages are estimated to be reduced by 0.25-0.5 percent, following an increase of one robot per 1,000 workers. These effects are significant between commuting zones. However, as the paper stresses, there are currently relatively few industrial robots in the US economy, and the effects have been limited. Accordingly, the results are dependent on the development in the future spread of robots. The response of employment will perhaps be different once the number of robots exceeds a critical threshold.

Studying 17 developed EU countries from 1993 to 2007, Graetz and Michaels (2017) find evidence suggesting that increased use of robots did not significantly reduce total employment within 14 selected industries. By exploiting novel panel data on robot adoption within the industries, they use an instrumental variables approach, exploiting robots' comparative advantage relative to humans in specific tasks, *replaceability*, as an instrument for robot densification. Graetz and Michaels find that increases in use of industrial robots is associated with increases in labor productivity. Evidence suggests that increased use of industrial robots have substantial effects on economic growth. Conservative estimates suggest a contribution of 0.37 percentage points, accounting for about one tenth of aggregate economy-wide economic growth. Further, evidence shows that increased robot densification is associated with increases in total factor productivity and wages, without imposing significant changes on overall employment. However, they do find suggestive evidence that robots did indeed reduce the employment share of low-skilled workers relative to middle- and high-skilled workers. Robots appear to reduce the share of hours worked by low-skilled workers, suggesting a change in the composition of the labor force, not in the overall employment. These findings are inconsistent with technological unemployment, and consistent with skill-biased technological change. Graetz and Michaels stress that industrial robots accounted for only 2.25 percent of the capital stock in robot-using industries in 2007, and thus, penetrated a limited part of the industries studied.

3 Empirical Methodology

Drawing on the literature presented in Section 2, we explore the relationship between industrial robots and employment outcomes within Norwegian manufacturing industries. Our approach is to explain changes in the probability of employment by developments in the use of industrial robots in the Norwegian manufacturing industry.

3.1 Main Outcomes from Previous Research

As emphasized by Keynes (1930) and Brynjolfsson and McAfee (2014), evidence of technological unemployment may occur in the presence of technological developments that make labor relatively less attractive. The concept of technological unemployment suggests that increasing use of industrial robots may reduce employment. However, Graetz and Michaels (2017) find no evidence of a significant reduction of employment within industries resulting from increased robotization relative to labor in EU countries. Further, they find that although increased robotization did not significantly reduce overall employment, there was evidence consistent with skill-biased technological change. Increased robotization appear to alter the relative shares of different skill-level groups, in favor of skilled workers and disfavor of unskilled workers. Simultaneously, Autor et al. (2013), Donoso et al. (2015), and Balsvik et al. (2015) find evidence that increased exposure to import competition have a negative effect on employment for the US, Spain, and Norway, respectively.

3.2 Empirical Approach

We use linear probability models to analyze the relationship between increased robotization and the probability of being employed. The dependent variable is binary, and has two possible outcomes; employed and unemployed. Thus, the probability of being employed is given by:

$$P(y=1|x) = \beta_0 + \beta_1 x_1 + ... + \beta_k x_k \tag{1}$$

Since an individual can be either employed or unemployed, β_j measures the change in probability of being employed when x_j changes, holding everything else fixed:

$$\Delta P(y=1|x) = \beta_j \Delta x_j \tag{2}$$

The linear probability model (LPM) is estimated by an ordinary least squares (OLS) regression[2]. Our model is specified as follows:

$$y_{ist} = \delta\, robots_{st} + \gamma\, competition_{st} + \pi\, skill_{ist} + \sigma\,(skill * robots)_{ist} + x'_{ist}\beta + \lambda\; year_t + \varepsilon_{ist}, \tag{3}$$

$$(i = 1,...,N;\; s = 1,...,S;\; t = [1996,...,2005]\ \&\ [2008,...,2015])$$

where y_{ist} is an indicator variable equal to one if individual i is employed in industry s at time t, and zero otherwise. We estimate the effect of robotization by the variable $robots_{st}$, which is defined as robot density, the number of operational industrial robots per 1,000 workers. Further, we include the ratio of import relative to domestic production in the respective industry, to control for exposure to foreign competition, $competition_{st}$. $skill_{ist}$ is a dummy variable indicating the level of education, and is equal to one if the individual has achieved higher education, and zero otherwise. $(skill * robot)_{ist}$ is an interaction term capturing the effect of robots on skilled workers. $\mathbf{x'}_{ist}$ is a set of control variables capturing observable individual specific characteristics. We have included Age and Age^2, a dummy for gender, $Female$, and $Education$, where education is the exact achieved educational level. $year_t$ is a set of yearly dummies, and ε_{ist} is the error term, which is normally distributed in an ordinary LPM. A more detailed description of the content of the variables, is provided in Sections 4 and 5.

One of the coefficients of main interest is δ, which describes the relationship between increased robot density and the probability of being employed. In order for technological unemployment to be present, this coefficient has to be negative. Further, another coefficient of main interest is σ, which represents the association of increased robot density on the probability of being employed for skilled workers. By including the interaction term, δ measures the association of increased robot density on the probability of being employed for unskilled workers. If skill-biased technological change is present, σ should be positive, while δ should be negative, to be consistent with previous research presented in Section 2. We estimate the relationship between robotization and the probability of being employed in two separate time periods, 1996 - 2005

[2] See e.g. (Wooldridge, 2012) for a detailed description of LPM and OLS.

and 2008 - 2015. This will be discuss in Section 5.

According to Acemoglu and Restrepo (2017), we need to assume that robotization is distinct from other industry-specific trends to draw inference about the relationship between robotization and the probability of being employed. We want to avoid concurrent effects which could influence the impact of robotization on the probability of being employed. Thus, if an industry increases its robot stock, the possibility of this industry to increase its capital stock will reduce our inference, because this can affect the probability of employment. In Section 6, we discuss whether this assumption holds.

3.3 Our Analysis

Previous research has analyzed the impact of robotization on aggregated employment within several industries. We have the opportunity to analyze the relationship between increased robotization and the probability of being employed in Norwegian manufacturing industries, exploiting individual level data from the Norwegian Labour Force Survey. Further, we exploit data on operational industrial robots provided by the International Federation of Robotics.

We exploit the variation in robot usage in different Norwegian manufacturing industries, to see how it affects the probability of being employed. A vital challenge in our analysis is possible endogenity problems. If our model specification excludes effects which are associated with the probability of employment and simultaneously correlated with robotization, we have a violation of Gauss-Markov assumption 4. Thus, we will obtain biased and imprecise estimations of robotization (Wooldridge, 2012). This Gauss-Markov assumption states that the expected value of the error term ε is zero given any values of the independent variables, $E(\varepsilon|x_1,x_2,...,x_k) = 0$. Unobservable effects, such as individual ability, may cause an omitted variable bias. When exploiting a survey-panel over several years, measurement errors and sample selection biases are likely to occur. All these challenges will be discussed in Sections 4, 5, and 6.

A problem with the linear nature of the LPM occurs if the estimated relationship is non-linear. If we estimate a non-linear relationship in a linear model, the linear model may produce predicted probabilities outside the interval between zero and one. A non-linear model differs from the LPM in the definition of the outcome variable y_{ist}. While the outcome variable represents a binary variable in the linear probability model, it represents a *latent* binary variable in the non-linear model, such that:

$$y_{ist} = 1, if y_{ist} > 0$$

$$y_{ist} = 0, if y_{ist} \leq 0$$

The difference implies that, while the LPM may estimate probabilities outside the interval between zero and one, the estimated probabilities from the non-linear model are given by a function, G, which takes on values strictly between zero and one, $1 < G(z) < 0$, for all real numbers z. This is given as:

$$P(y = 1|x) = G(\beta_0 + \beta_1 x_1 + ... + \beta_k x_k) = G(\beta_0 + x\beta)$$

We prefer the probit model over a logit model, because we then can assume that the error term from Equation 3, ε_{ist}, has a constant standard deviation of $\sigma_\varepsilon^2 = 1$. In the probit model, G is the standard cumulative normal distribution function for the probability of being employed (Wooldridge, 2012). The probability of an individual i being employed in a given industry s at time t is given as:

$$P(y_{ist}|robots_{st},\ competition_{st},\ skill_{ist},\ (skill * robots)_{ist}, x'_{ist},\ year_t) \tag{4}$$

$$= \Phi[(\delta\ robots_{st} + \gamma\, competition_{st} + \pi\, skill_{ist} + \sigma\,(skill * robots)_{ist} + x'_{ist}\beta + \lambda\ year_t)]$$

where Φ is a cumulative standard normally distributed function. Since the probability model is non-linear, an OLS estimation does not apply. Therefore, the estimation depends on the maximum likelihood estimation (MLE)[3]. However, the probit model does not solve the potential problem if there exists non-normality of the error term or omitted variable bias in the LPM. Another problem with the estimation methods, can occur if the dependent variable has a skewed distribution for the outcomes. We deal with this problem by redefining the dependent variable, which will be discussed in Sections 5 and 6.

Reverse causality between robotization and the probability of being employed, may cause endogeneity in the model. We expect that robotization will affect the probability of being employed, but the relationship may be the opposite. Acemoglu and Restrepo (2017) utilize an instrumental variables approach (IV), where possible endogeneity is avoided by using European robot

[3]See e.g. Wooldridge (2012) for a detailed description of the probit model and MLE.

density as an instrument for US robot density. Similarly, we use an exogenous instrument of robotization instead of Norwegian robotization. The IV approach follows the same setup as the LPM model in a 2SLS regression[4]. To be able to run a 2SLS regression, we need an instrument which satisfies two requirements, relevance and exogeneity, respectively given by:

$$Cov(z|x) \neq 0 \tag{5}$$

$$Cov(z|\varepsilon) = 0 \tag{6}$$

In order to have a valid instrument, the instrument, z, has to be correlated with robotization in Norway, x, and simultaneously be uncorrelated with the error term, ε.

We would ideally used a fixed effects model to analyze the effects of robotization on employment. By using fixed effects, we could control for unobservable individual time-consistent effects. However, since we are restricted to a maximum of two observations on each individual, a fixed effects approach is not feasible. Hence, we cannot interpret the effect of robotization on the probability of employment as a causal effect. Instead, we analyze what increased robotization is associated with in terms of employment outcomes. We feel confident that our model can shed light on the relationship between robotization and the probability of being employed.

To the best of our knowledge, the impact of industrial robots on employment in Norway, has not previously been studied. By exploiting the developments in robotization within the Norwegian manufacturing industry, we seek to provide new insights into how the use of robots impact employment. Further, we will also touch on whether skill-level, and thus education, is important in the interaction with robots. We hope our thesis will provide a basis for future research on the intriguing topic of how robots impact employment.

The literature on the effect of industrial robots on employment, shows limited or no decline in overall employment as a result of an increase in robot density. However, evidence suggest a change in the skill-composition of the work-force, in disfavor of unskilled workers. Previous studies have focused on the US and EU. On the one hand, there are many similarities between Norway and the previously studied countries, which suggests that our findings should be comparable. On the other hand, Norway has a smaller manufacturing industry compared to the previously studied countries. Therefore, there may be a different relationship between employ-

[4] See Wooldridge (2012) for a detailed description of the IV approach.

ment and robotization in Norway than the previous studies indicate. Our analysis is divided into two time periods 1996 - 2005 and 2008 - 2015, to avoid a break in the time-series and skewness of the employment distribution.

4 Robots in Norway

The Norwegian manufacturing industry has declined since the 1970s, and today accounts for about 9 percent of the GDP in mainland Norway. Between 1974 and 2012, 139,000 manufacturing employees left the industry. In 2012, roughly 247,000 were employed in manufacturing industries, accounting for about 11 percent of total employment. Increased communication and international trade have intensified competition, and competition from low-cost countries have caused businesses to close down or move production abroad. By focusing production on niche industries, in which Norway has comparative advantages, some Norwegian manufacturing industries remain competitive in a globalized world. These industries are often characterized by high-technology requirements, exploiting high competence within the Norwegian population, in addition to local resources (Ministry of Trade, Industry and Fisheries, 2001; Rusten, Potthoff, & Sangolt, 2013). Hence, the Norwegian manufacturing industry has good prerequisites for implementing industrial robots.

We exploit data on industrial robots provided by the International Federation of Robotics. The original data contains information on the stock of delivered and operational robots by industry, country, and year. Over the period 1993 - 2015, the data covers 40 single countries and regions; Americas, Europe, Asia/Australia, and Africa. The data collected by the International Federation of Robotics, is based on yearly surveys of nearly all industrial robot suppliers world-wide (International Federation of Robotics, 2014). We primarily use data on Norway, but also exploit data on Sweden and Germany to compare developments in the three countries over time. The data contains information on the number of delivered robots, and the robot stocks are calculated on the basis of previous stocks of operational and delivered industrial robots.

The International Federation of Robotics defines an industrial robot according to the International Organization for Standardization definition, ISO 8373:2012. An industrial robot is defined as: "An automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications" (International Federation of Robotics, 2014, p. 29). To elaborate on the features required to be defined as an industrial robot, *reprogrammable* implies that the auxiliary functions or programmed motions can be changed without physical alteration. The ability of being adapted to a different application with physical alteration is captured by the *multipurpose* feature, while *axis* refers to the direction used to specify the robot motion in a linear or rotary mode. The International Federation of Robotics operates with an average of 12 years service life for industrial robots. Hence, a robot is immediately withdrawn from the operational stock after 12 years, although the actual service life may be longer. This assumption imposed by the International Federation of Robotics, represents a weakness in the robot data, as only the predicted, and not the actual operational stock is considered. Hence, we do not know how well the stocks supplied by the International Federation of Robotics, compare to the actual stocks in Norway, and this may cause measurement errors in the data.

Robots are classified by the industry in which they operate. The International Federation of Robotics classifies robots into industrial branches by their own classification. This classification is based on, however, not entirely consistent with the International Standard Industrial Classification of All Economic Activities (ISIC) revision 4 (International Federation of Robotics, 2014). This classification inconsistency imposes an issue when connecting the robot data to the data from the Norwegian Labour Force Survey, which classifies industries according to ISIC 3 and 3.1. In order to utilize both the robot data and the survey data simultaneously, we had to overcome this challenge. By manually linking industries and their respective classification codes, we have connected industries over the International Federation of Robotics and ISIC revisions 3, 3.1, and 4. The correspondence between the different classifications is presented in Table A1 in Appendix, and we emphasize that only the industries with an obvious link have been connected. The connection of the industries have been conducted on the basis of available information retrieved from the International Federation of Robotics (2014) and the United Nations Statistics Devision (2017).

4.1 Developments in the Manufacturing Industry

Establishing a context, we compare Norway to similar industrialized countries in terms of the development in operational industrial robots relative to the development in industrial employment. Sweden and Germany have traditionally been larger industrial nations than Norway, and thus, constitute interesting comparisons in terms of operational industrial robots. By indexing the developments in operational industrial robots and industry employment, we can compare the three countries. However, we stress that the source of the employment statistics used in the employment index in Norway differs from the source used for Sweden and Germany. The statistics for Sweden and Germany are obtained from the EU KLEMS database. Unfortunately, statistics for Norway are not included in this database. Thus, we use aggregated employment figures for all manufacturing industries in Norway obtained from Statistics Norway.

The index in Figure 1, presents the development in operational robots in Norwegian manufacturing industries and the contemporary development in employment within the same industry. As evident from the figure, the Norwegian manufacturing industry has since the turn of the century, seen an increase in the number of operational robots relative to the base year 1995. Figure 1 displays a slight decline in operational industrial robots from 1995 towards 2000, followed by a persistent increase throughout 2007. This development is likely to be explained by the development in robot technology, and a subsequent decline in the price level. As robot technologies improved, demand increased, and hence, prices declined. After 2008, we observe a declining trend in the number of operational robots. According to the International Federation of Robotics, industrial robots are removed from the stocks after 12 years. Thus, the decline in the number of robots in the operational stock, is likely to be connected to the exclusion of robots from the stocks. This may be a result of the financial crisis in 2007-2009, the Great Recession. After the turmoil in financial markets following the crisis, banks restricted lending, which contributed to limit the opportunities of investing in new robots (Norges Bank, 2008). Thus, the discarded robots were not necessarily replaced. However, the exclusion from the stock is by definition automatic. Thus, we do not know whether the robots were actually removed, or if they continued to be operational. The difference between the baseline level in 1995 and 2015, shows an increase in the number of operational industrial robots of approximately 70 percent.

The employment in the Norwegian manufacturing industry, fluctuates around the 1995-level. Following a slow increase between 1995 and 1998, employment decreases relative to the 1995-level from 1999 to 2007. In 2007, employment in Norwegian manufacturing industries experience a sharp increase, reaching a peak in 2008 ahead of a decline in the following years.

Summarizing the development in Figure 1, the stock of operational robots increases compared to the 1995-level. Employment fluctuates around the 1995-level, but is in 2015 slightly below the baseline level. The overall picture shows a strong growth in operational robots, and a slight decrease in manufacturing employment.

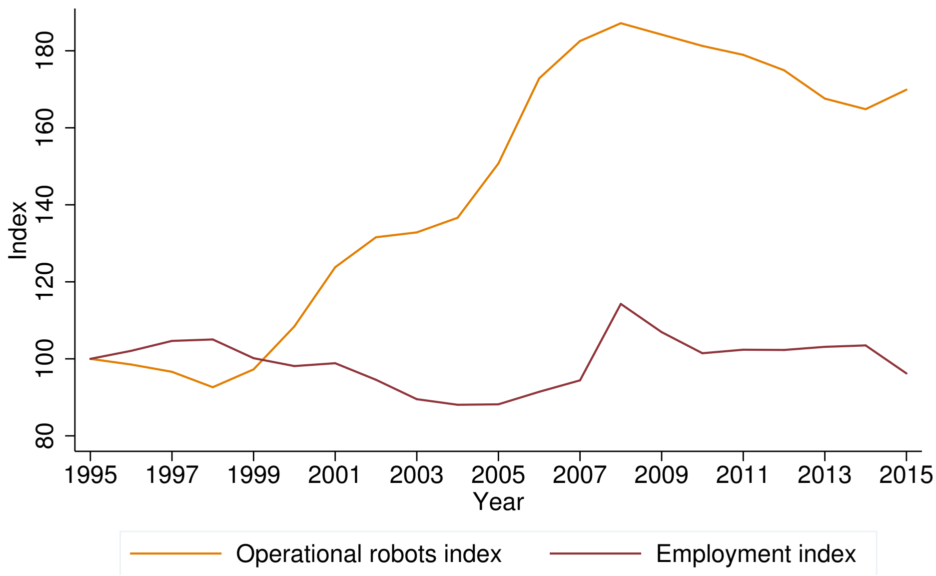

Figure 1: Operational robots and employment in Norwegian manufacturing 1995 - 2015.
Note: The figure displays the development of operational industrial robots and industry employment in Norwegian manufacturing industries 1995-2015. Data on the stock of industrial robots is obtained from the International Federation of Robotics. Data on employment is obtained from ssb.no.

Similarly to Figure 1 for Norway, Figures 2 and 3 show the development in operational robots and employment in manufacturing in Sweden and Germany, respectively. We emphasize that the index scales differ between the three figures, and hence, differences in employment development may not be clear at first sight. The figures show that the development in the two countries is similar, exhibiting a steady increase in robots persistent over the 20-year period. In Sweden, the number of operational industrial robots increased by roughly 150 percent between 1995 and 2015, whereas the corresponding increase in Germany was in excess of 200 percent. The employment indexes in both countries, show a declining development, simultaneously with the increase in operational robots. Compared to the 1995-level, the decline in 2015 in Swedish and German manufacturing employment is about 20 and 10 percent, respectively. The decline in employment is evidently slower in Germany compared to Sweden. The developments in Figures 2 and 3, show that increased use of industrial robots within manufacturing is associated with a slight decline in the manufacturing employment.

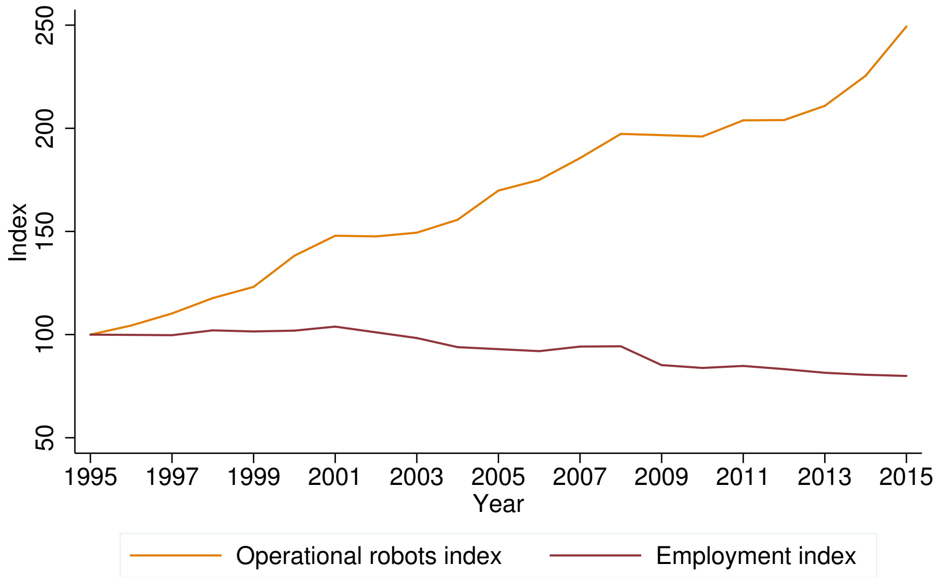

Figure 2: Operational robots and employment in Swedish manufacturing 1995 - 2015.
Note: The figure displays the development of operational industrial robots and industry employment in Swedish manufacturing industries 1995-2015. Data on the stock of industrial robots is obtained from The International Federation of Robotics. Data on employment is obtained from the EU KLEMS database.

Comparing the three countries, the development in Norway stands out from the corresponding developments in Sweden and Germany. While Sweden and Germany exhibit steadily increasing growth in operational robots from the baseline year 1995, the development in Norway is more divergent. The employment index follows the same development. In Norway, employment is volatile around the baseline level, while Sweden and Germany follow slowly declining developments. The magnitude of the changes in robots is evidently higher in Sweden and Germany compared to Norway. This suggests that the investment in and introduction of industrial robots in industry operations have been persistent in Sweden and Germany, while Norwegian industry have been more cautious and perhaps restrictive in implementing robots.

Comparing the robot densities in Norway, Sweden and Germany, differences in the scope of robot usage become evident. The developments in robot density between the three countries are shown in Figure 4. Over the 20-year period, the robot density have increased by nearly 1.5 robots per 1,000 workers in Germany, while the corresponding increase in Sweden is above 1 robot per 1,000 workers, relative to the 1995 baseline. In comparison, Norway exhibits only a slight increase in robot density over the period. The increase in the Norwegian robot density is approximately 0.1, equivalent to a one tenth of the growth for Sweden, and 7 hundreds of the growth for Germany. Further, as the densities in Sweden and Germany display steady positive growth, the Norwegian density maintains a stable level. This stable level indicates that the relationship between the number of robots and employees in the industry, remains consistent over the period.

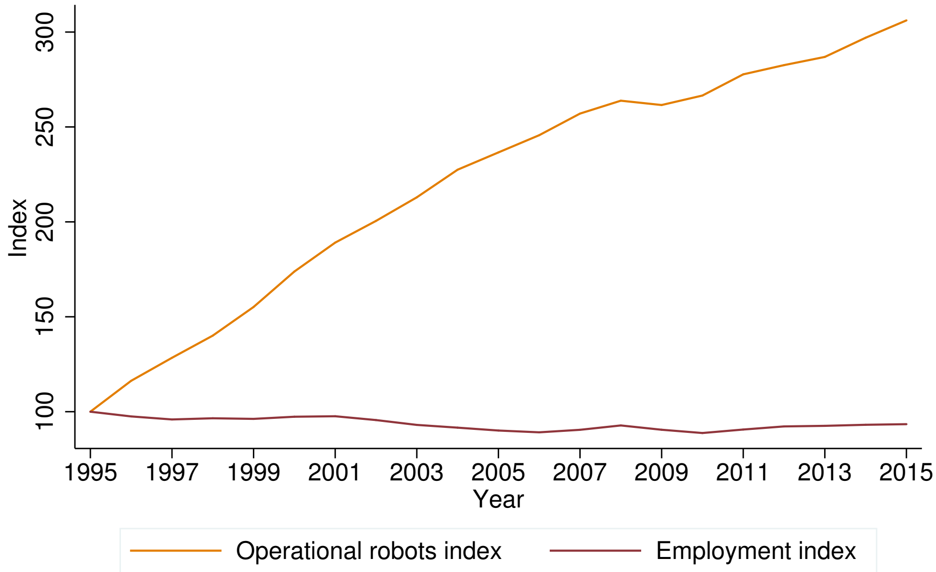

Figure 3: Operational robots and employment in German manufacturing 1995 - 2015.

Note: The figure displays the development of operational industrial robots and industry employment in German manufacturing industries 1995-2015. Data on the stock of industrial robots is obtained from The International Federation of Robotics. Data on employment is obtained from the EU KLEMS database.

The developments presented in Figures 1-4, indicate that the development in Sweden and Germany show increased use of industrial robots and declining employment. This is to a smaller extent the case for Norway. The development in Norway, implies that a negative association between robotization and the probability of being employed, appears unlikely. However, we have used figures for the aggregated manufacturing industry, and thus, there may be differences between different subindustries within manufacturing.

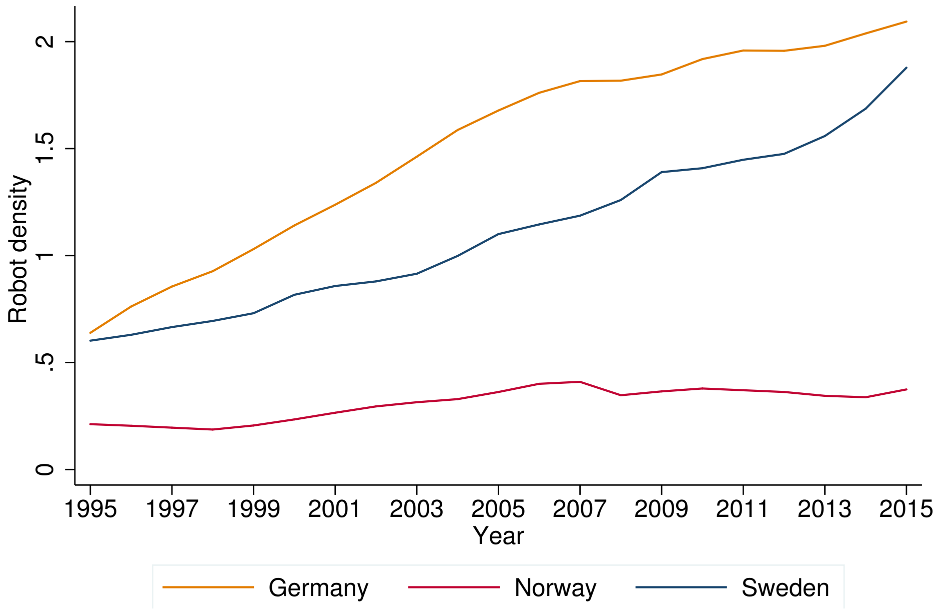

Figure 4: Development in robot densities 1995 - 2015

Note: The figure displays the development in robot densities in Norway, Sweden, and Germany in the period 1995 - 2015. The robot density is calculated as number of operational robots in the manufacturing industry divided by the employment in the industry. Data on the stock of industrial robots is obtained from The International Federation of Robotics for all countries. Data on employment is obtained from ssb.no for Norway, and from the EU KLEMS database for Sweden and Germany.

4.2 Norwegian Manufacturing Industries

Figures 5 and 6 present developments in operational industrial robots and employment within a subsample of Norwegian manufacturing industries in the time periods 1996 - 2005 and 2008 - 2015. The different industries display differing developments in the two periods. Figure 5 shows that the development within specific Norwegian manufacturing industries between 1996 and 2005 differ substantially. The *Wood and furniture*, *Minerals* and *Automotives and vehicles* industries show a sharp increase in robots combined with a gradual decline in employment, while the *Metal products* industry show an increase in both robots and employment over the period. The *Minerals* and *Automotives and vehicles* industries are in particular exhibiting a sharp increase in robots relative to the baseline after 2000.

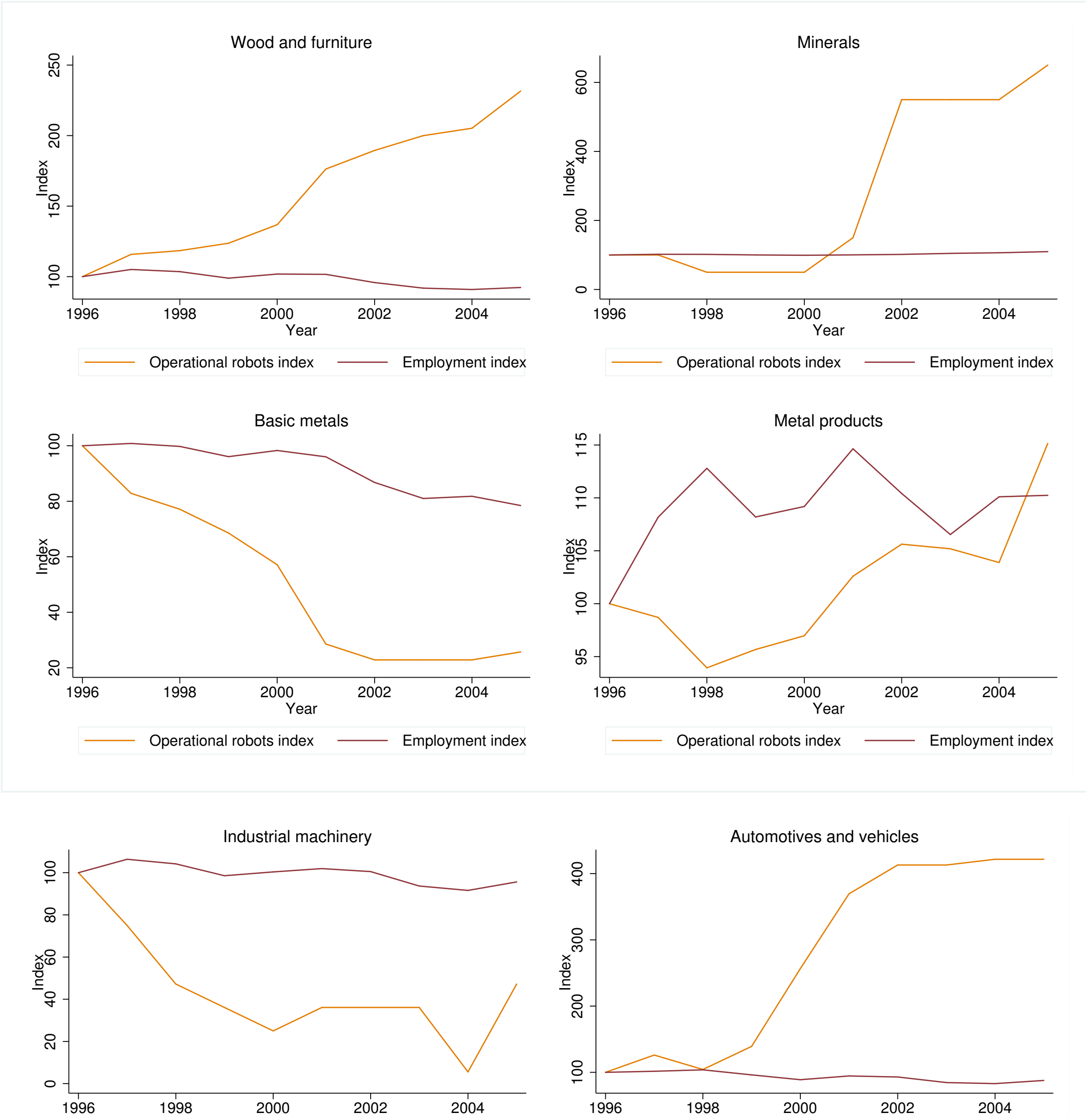

Figure 5: Developments in operational robots and employment by industry 1996 - 2005.

Note: This figure compares the developments in the stock of operational industrial robots and employment in the period 1996 - 2005 within the subindustries from the Norwegian manufacturing industry present in our sample. The *Rubber and plastic* industry has been excluded from this figure due to limited development in the period. The industries are specified in Table A1 in Appendix A. The data is obtained from the International Federation of Robotics and Statistics Norway.

Considering the development in operational industrial robots in the *Minerals* and *Automotives and vehicles* industries, there is a drop in robots from 2012 to 2014, evident in Figure 6. A similar development is evident in the *Metal Products* industry, which shows an increase in industrial robots in the period 1996 - 2005, and a subsequent drop in robots in the period 2008 - 2015. There is a 12 year difference between the sharp increase around the 2000s and the subsequent decrease in the mid-2010s. The 12-year-gap between increased robot stocks and subsequent declines, corresponds to the robot service life assumption defined by the International Federation of Robotics. Thus, the robots included between 2000 and 2002, were automatically excluded from the stock between 2012 and 2014. However, the robots may be in operation past the 12-year life span, and the presented graphs may not represent the actual developments and stocks of operational robots.

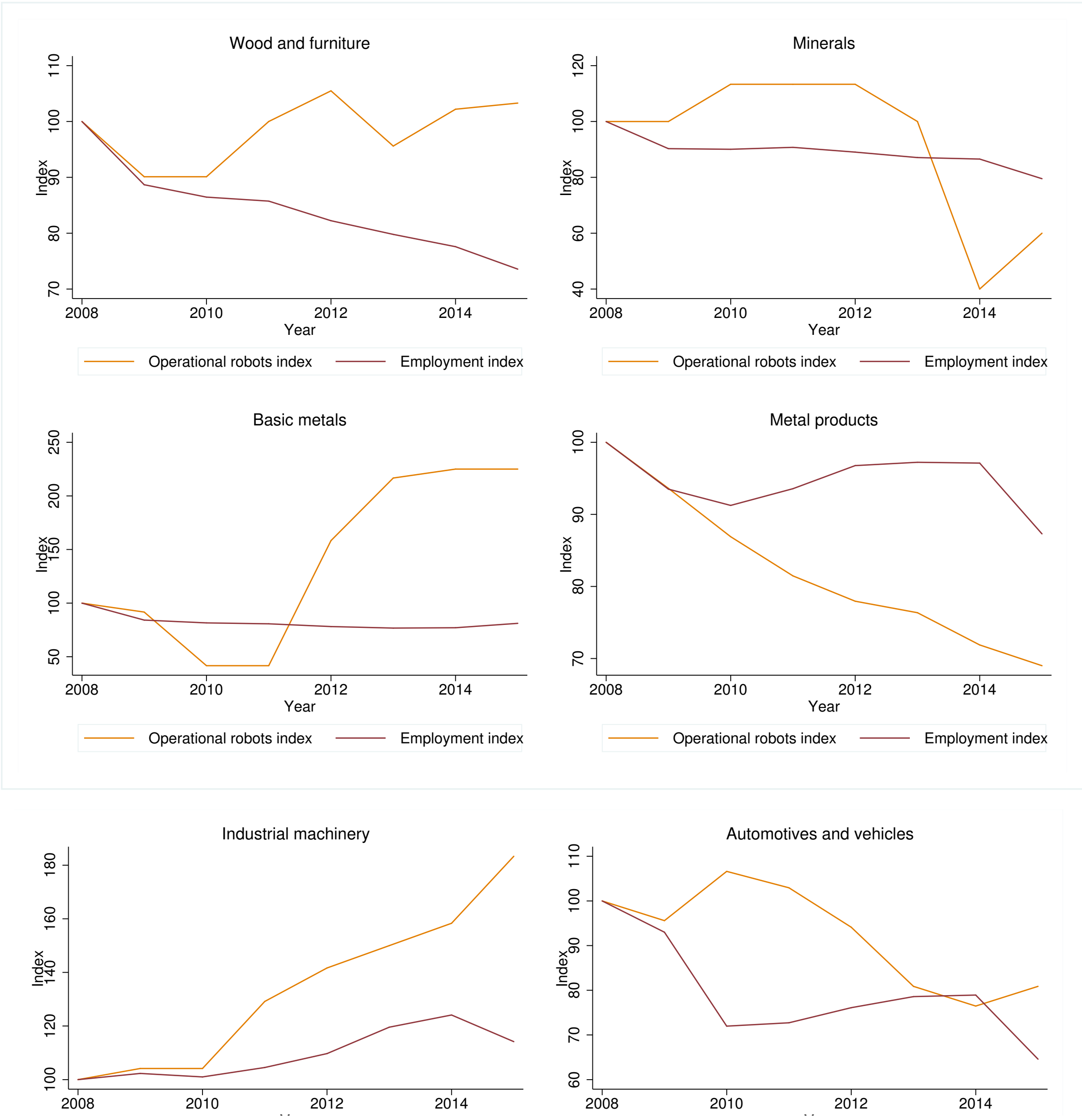

Figure 6: Developments in operational robots and employment by industry 2008 - 2015.

Note: This figure compares the developments in the stock of operational industrial robots and employment in the period 2008 - 2015 within the subindustries from the Norwegian manufacturing industry present in our sample. The *Rubber and plastic* industry has been excluded from this figure due to limited development in the period. The content of the industries is specified in Table A1 in Appendix A. The data is obtained from the International Federation of Robotics and Statistics Norway.

The *Basic metals* and *Industrial machinery* industries show similar developments in the two periods. Both industries experience a decline in the robot stocks in the period 1996 - 2005, and a subsequent increase between 2008 and 2015. The development in employment is gradually declining for both industries in the period 1996 - 2005, whereas there is a slight increase in employment in the *Industrial machinery* industry in the 2008 - 2015 period, while the *Basic metals* employment continues to decline slightly.

We have not included the *Rubber and plastic* industry in the Figures 5 and 6. Before 2005, the industry had no industrial robots according to the International Federation of Robotics. Therefore, there is no comparison between the time periods. Further, from 1996 to 2005, the employment decreased by 20 percent in the industry. In the period 2005 - 2007, firms invested heavily in advanced robots to optimize their production processes. In the light of the 2007-2009 financial crisis, the decreasing demand for rubber and plastic products from several other industries, caused the number of operational robots to stagnate (International Federation of Robotics, 2009). However, after the financial crisis, the number of operating robots increased gradually. In the time period 2008-2015, employment in the industry decreased by 21 percent.

The Norwegian manufacturing industries may be dependent on each other, and on the developments in both the domestic and the international economy. As evident in the Figures 5 and 6, the developments in operational robots of related industries may follow each other, such as the *Basic metals* and *Industrial machinery*. Figures 5 and 6 show that the developments in subindustries, differ from the developments in the aggregated manufacturing industry displayed in Figure 1. The presented subindustries represent a subsample of the Norwegian manufacturing industries, and the development in other subindustries may differ from the subindustries presented here.

Figures 5 and 6 showed the growth in operational robots, however, we are also interested in the developments in robot density for analysis purposes. Figures 7 and 8 display the differences in robot densities between subindustries in the Norwegian manufacturing industry in the two periods 1996 - 2005 and 2008 - 2015. This development is not directly comparable to the Norwegian robot density presented in Figure 4, as we in these figures, look at a selection of subindustries, not the aggregated manufacturing industry. This is because our sample only includes industries at a two-digit level. These industries are more robot intensive, as the International Federation of Robotics provides data on industries with few robots at a rougher level.

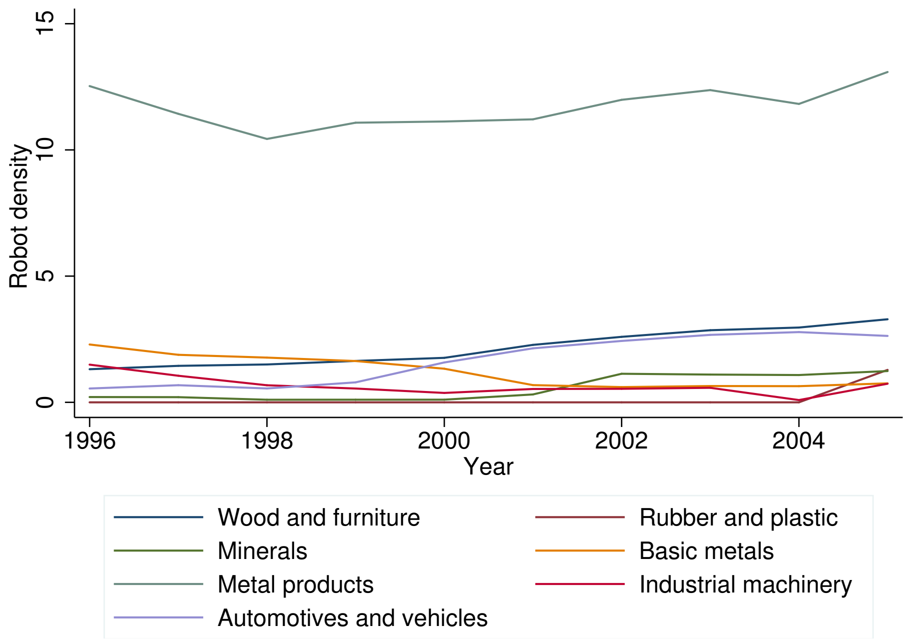

Figure 7: Robot density in Norwegian manufacturing industries in the period 1996 - 2005

Note: The figure shows the developments in robot densities for the subindustries present in the sample we use in our empirical analysis. Data on the stock of industrial robots is obtained from The International Federation of Robotics. Data on employment is obtained from Statistics Norway.

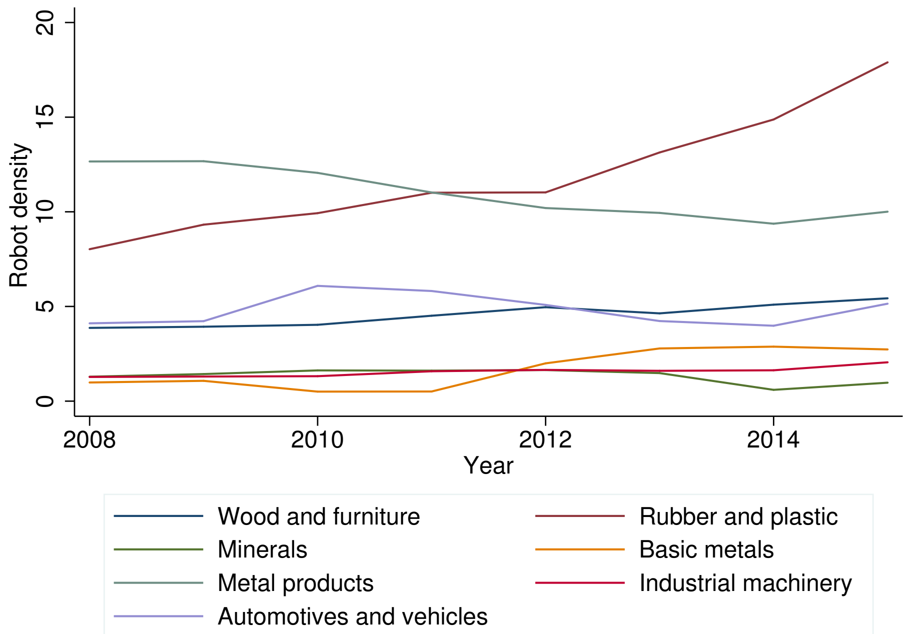

Figure 8: Robot density in Norwegian manufacturing industries in the period 2008 - 2015

Note: The figure shows the developments in robot densities for the subindustries present in the sample we use in our empirical analysis. Data on the stock of industrial robots is obtained from The International Federation of Robotics. Data on employment is obtained from Statistic Norway.

As evident from Figure 7, the robot densities between 1996 and 2005 differ between the industries, where the *Wood and furniture*, *Minerals*, and *Automotives and vehicles* display increased robot densities, while *Basic metals* and *Industrial machinery* experience a decline. The *Metal products* industry had the highest robot density of about 12 robots per 1,000 workers, a high density compared to the density for the aggregated manufacturing industry. Figure 8 shows that the variation in robot density has increased between the 1996 - 2005 and 2008 - 2015 periods, and the *Industrial machinery* industry emerged as the most robot dense industry in the 2008 - 2015 period. The robot density in the *Industrial machinery* industry, increased by a substantial 10 robots per thousand workers over the period. The development in the other industries was relatively stable. While the *Wood and furniture*, *Automotives and vehicles*, and *Basic metals* industries experienced a slight increase, the *Metal products* and *Minerals* industries declined over the 2008 - 2015 period. The *Industrial machinery* industry remained at a stable level. Finally, we exploit this variation in robot densities in different Norwegian manufacturing industries in our analysis.

5 The Norwegian Labour Force Survey

5.1 The Survey

The Norwegian Labour Force Survey is a comprehensive interview survey, based on a representative sample of the Norwegian population eligible for labor force participation. The survey provides panel data consisting of a representative selection of the population aged 16-74 (from 2006; 15-74). The individuals selected to participate, are members of randomly selected households from all municipalities, drawn from the Norwegian address register. The individuals are interviewed quarterly over eight consecutive quarters. Each panel is based on a selection of 24,000 individuals, where dropouts are not replaced, and thus, the net selection in each panel varies within 80-95 percent of the original sample (Bø & Håland, 2002). The advantage with this panel survey, is the opportunity it provides to follow different individuals over a given time period. The survey reveals the sampled individuals' connection to the labor market, and the objective is to describe labor market developments. Important developments addressed by the survey includes employment, unemployment, and temporary hiring. Additionally, the survey provides information on individual characteristics including age, education, and gender, which are included in our model specification. Education describes the education level achieved at the time the participant is surveyed, and varies from completed secondary school to a professor level (Bø & Håland, 2015).

The Norwegian Labour Force Survey is subject to several breaks in the time-series, due to major revisions, in 1996 and 2006, and the lack of panels between 1992 and 1995 and 2004 and 2005. We find it reasonable to avoid complicating breaks and revisions in our analysis, and hence, we have divided our analysis into two time periods, 1996 - 2005 and 2008 - 2015.

5.2 Selection of Data for Our Analysis

The data in our analysis, contains information on individuals in the Norwegian manufacturing industry, including which industry they are connected to, and their status in the labor force (employed, temporarily employed, or unemployed). While this data i reported quarterly, the data from the International Federation of Robotics is reported annually. Thus, in order to connect the two data sources, we aggregate the survey data to annual observations. Hence, observations that lack information on employment status or industrial connection, are excluded from our sample.

We merge the data from the Norwegian Labour Force Survey with the data from the International Federation of Robotics. In order for the periods before and after the time-series break in 2006 to be comparable, we select only industries that matches the industries in the robot data in both periods. Consequently, our sample is reduced, and thus, we obtain a net selection of industries smaller than if we were to analyze only one of the time periods. We consider the possibility of comparing the same industries before and after the break in the time-series as interesting, and therefore justifies the limitations imposed by our decision.

According to the Norwegian Labour Force Survey's definition of unemployment; an unemployed person cannot have income-generating work, have been trying to get work recently, and have to be available for work (Bø & Næsheim, 2015). In aggregating the quarterly observations to annual, we have defined an individual as unemployed if he/she is unemployed in two or more quarters. Hence, to capture unemployed persons that do not qualify to be unemployed by the survey, we have included both persons defined as unemployed and persons registered outside the labor force in our measure of unemployed. This assumption may overestimate the number of unemployed persons, as some of the persons registered outside the labor force may be unable to work or retired. However, we assume this measure to be closer to the true unemployment rate. There are no mechanisms that control whether the information provided by the individuals is correct, and hence, people may provide wrong or false information. As a consequence, the Norwegian Labour Force Survey have attempted to overcome the problem of people conveying false information, by changing the structure and content of the questionnaires, limiting the possibilities of falsifying answers (Bø & Håland, 2002).

Table 1 compares the unemployment rate in our final sample to the unemployment rate given by NAV statistics, and shows how many panels that are present in a given year. The average unemployment rate in our sample, is smaller than our constructed NAV registered unemployment for manufacturing in both time periods, although the two rates are closer in the 2006 - 2015 period. We emphasize that the NAV unemployment differs from the unemployment derived from the Norwegian Labour Force Survey. The survey unemployment is derived from the sampled population, and includes all individuals that satisfies the requirements to be defined as unemployed. While the NAV unemployment, which is based on the same requirements, includes only individuals registered at NAV as unemployed. Therefore, the unemployment in our sample should be higher than the NAV unemployment. However, this is not displayed in Table 1. The sample rate includes only the subsample of industries present in our final sample, while the NAV rate includes all Norwegian manufacturing industries. Although the included industries differ, and thus, may have different impacts on the unemployment rate, the NAV rate provides an indication of the actual unemployment rate, and sheds light on the skewness of the employment distribution in our sample.

Table 1: Unemployment rates

1996-2005				2006-2015			
Year	Sample rate	NAV rate	Panels	Year	Sample rate	NAV rate	Panels
1996	0.040	0.080	1	*2006*	*0.014*	*0.034*	*4*
1997	0.019	0.064	5	*2007*	*0.028*	*0.024*	*8*
1998	0.027	0.050	8	2008	0.039	0.024	11
1999	0.053	0.060	11	2009	0.053	0.049	11
2000	0.044	0.069	11	2010	0.039	0.053	11
2001	0.024	0.050	10	2011	0.039	0.045	11
2002	0.000	0.053	10	2012	0.049	0.042	11
2003	0.000	0.072	11	2013	0.010	0.042	11
2004	0.000	0.067	8	2014	0.021	0.044	11
2005	0.000	0.054	4	2015	0.028	0.057	9
Average	0.021	0.062	8	Average	0.032	0.041	10

Note: The sample unemployment rate is calculated from our final sample as $Samplerate = Unemployed/Workforce$, where the workforce is the sum of employed and unemployed. The NAV rate is calculated as $NAVrate = NAV\ unemployed/(NAV + registered\ employment\ statistics)$, using the registered unemployed at NAV. We emphasize that whereas the sample unemployment rate is calculated for the subsample of industries in our final sample, the NAV rate comprise all Norwegian manufacturing industries. The data on registered unemployment used in the NAV rate is obtained from nav.no, while the registered employment statistics is obtained from ssb.no. The years 2006 and 2007 are excluded from our sample.

Including the number of panels present in each year in Table 1, we observe that the two unemployment rates are closer when the number of panels, and hence the number of observations increases. One obvious issue is the absence of unemployed persons in the period 2002 - 2005, combined with few observations. This problem is likely to occur as a result of attrition of unemployed workers from the sample, and imposes a weakness in our analysis. The low unemployment rate in our sample is particularly evident in the last survey rounds in a given panel, as seen between 2002 - 2007. This contributes to skew the sample towards being employed. As evident from Table 1, on average, between 97 and 98 percent of the observations from our samples in the periods 1996 - 2005 and 2008 - 2015 are employed. According to Hellevik (2009), very skewed distributions of the dependent variable do not create problems, and hence a linear regression on a binary dependent variable is appropriate. However, this depends on the sample size, where the problem is likely to be larger when the sample size is smaller. By excluding the years 2006 and 2007 from the time period 2008 - 2015, we obtain a less skewed sample, although we lose observations. However, in the time period 1996 - 2005, we want to obtain all possible observations due to missing panels. Therefore, we want to keep each year in this time period.

5.3 Descriptive Statistics

Our sample in the period 1996 - 2005, includes 7,572 observations, while our sample in the period 2008 - 2015 includes 5,796 observations. The reason why we obtain a larger sample in the first time period, is because manufacturing employment have been reduced over the time periods, and the exclusion of the two years 2006 and 2007. As a consequence, there are fewer manufacturing workers surveyed in the last time period to ensure a representative sample in the survey, despite more panels present in the last time period. This results in fewer observations in our sample in the last time period. Table 2 displays descriptive statistics from our final samples in the time periods 1996 - 2005 and 2008 - 2015.

The average worker in the period 1996 - 2005 is 40 years old, 82 percent likely to be male, and 85 percent likely to have a maximum of high school education. 50 percent of the individuals in our sample, are either employed in the *Wood and furniture* industry or the *Automotives and vehicles* industry. However, the distribution is not representative for the manufacturing labor force in Norway, and is caused by the lack of correspondence of the industries throughout the two time periods.

In the time period 2008 - 2015, the age of the average worker increases slightly, to just below 43 years, whereas the probability of being male remains the same as in the period 1996 - 2005. One interesting difference between the two periods is the increase in the mean of skilled workers. The mean number of skilled observations increases by 5 percentage points between the 1996 - 2005 and 2008 - 2015 periods, suggesting that the demand for skilled workers may have increased in the latter period. Between 2008 and 2015, 40 percent of our sample is employed either in the *Wood and furniture* industry or in the *Automotives and vehicles* industry.

Table 2: Descriptives for variables from the Norwegian Labour Force Survey

	Time period 1996-2005				Time period 2008-2015			
VARIABLES	N	Mean	Min	Max	N	Mean	Min	Max
Age	7,572	40.08	16	74	5,796	42.70	15	74
Female	7,572	0.176	0	1	5,796	0.177	0	1
Skilled	7,530	0.150	0	1	5,771	0.205	0	1
Industries	N	Mean	Min	Max	N	Mean	Min	Max
Wood and furniture	7,572	0.253	0	1	5,796	0.199	0	1
Rubber and plastic	7,572	0.069	0	1	5,796	0.099	0	1
Minerals	7,572	0.062	0	1	5,796	0.084	0	1
Basic metal	7,572	0.106	0	1	5,796	0.088	0	1
Metal products	7,572	0.114	0	1	5,796	0.189	0	1
Industrial machinery	7,572	0.152	0	1	5,796	0.129	0	1
Automotives and vehicles	7,572	0.244	0	1	5,796	0.212	0	1

Note: The table presents descriptive statistics for the individuals employed in the industries present in our sample. Skilled counts every observation with a recorded skill level, and displays the mean value of observations with a skill level equal to a completed Bachelor's degree or higher.

6 Results

6.1 Analysis of Robotization

In the analysis of robotization on the probability of being employed, we include six models, (1) to (6), as seen in Tables 3 and 4. The robotization coefficient represents the percentage point change in the probability of being employed associated with a one unit increase in robot density. The models included start from the basic model (1), which estimates the correlation between increased robotization and the probability of being employed. In model (2), we add controls for individual characteristics that affect the probability of employment, while in model (3), we add yearly dummies to control for year specific effects. Model (4), in addition to individual characteristics and yearly dummies, includes a proxy for exposure to import competition. Model (5) includes a variable defining the skill level of the worker, and an interaction term between skill and robotization, in order to capture the relationship between increased robotization and different skill levels. Finally, model (6) controls for skill, the interaction term between robotization and skill, and competition. We analyze the models considering a one unit increase in robot density (e.g. an increase in robot density from 0.5 to 1.5). In a Norwegian context, a one unit change in robot density is a quite large change. As visible in Figure 4 in Section 4, the robot density in Norway has remained low compared to Sweden and Germany, and only experienced a 0.1 unit increase in robot density over the period 1995 - 2015. This change is far below a one unit change, and thus, the magnitude of the coefficients presented in the following should be considered with this in mind. Hence, we emphasize that a one unit increase in the robot density in Norway is a substantial increase in light of the development in robot density over the past 20 years. However, in the industries in our sample, the robot density tend to be higher than the aggregated manufacturing level.

6.1.1 Time period 1996 - 2005

Table 3 displays the results from the LPM regressions. The result from the basic model (1), shows that a one unit increase in robot density is associated with a 0.1 percentage point higher probability of being employed. The result is statistically significant, and controlling for individual characteristics and import competition does not alter the result in model (4). The positive association between increased robotization and employment probability, indicates that technological unemployment is not present. However, the result is not economically significant, and in practice, unlikely to have any impact on the probability of being employed. In this period, as shown in model (6), increased robotization is not associated with changes in the probability of being employed, neither for unskilled nor skilled workers, after controlling for the interaction between robotization and skill. This indicate that there are no skill-biased impacts of robotization in this period.

Table 3: Dependent variable: Probability of being employed in the time period 1996 - 2005

	(1)	(2)	(3)	(4)	(5)	(6)
Robotization	0.0011*	0.0017**	0.0012*	0.0011*	0.0004	0.0003
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0010)	(0.0010)
Robotization × Skill					0.0011	0.0011
					(0.0012)	(0.0012)
Age		0.0167***	0.0167***	0.0166***	0.0166***	0.0166***
		(0.0017)	(0.0017)	(0.0017)	(0.0017)	(0.0017)
Age^2		-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0002***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Female		-0.0173**	-0.0176**	-0.0179**	-0.0173**	-0.0177**
		(0.0057)	(0.0057)	(0.0057)	(0.0057)	(0.0057)
Education		0.0014***	0.0014***	0.0014***	0.0011***	0.0011***
		(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Competition				-0.0056		-0.0057
				(0.0070)		(0.0070)
Skill					0.0118+	0.0120+
					(0.0063)	(0.0063)
Constant	0.9680***	0.6640***	0.6550***	0.6600***	0.6570***	0.6620***
	(0.0025)	(0.0335)	(0.0370)	(0.0370)	(0.0369)	(0.0369)
Yearly effects			✓	✓	✓	✓
Observations	7572	7530	7530	7530	7530	7530

$^+ p < 0.1$, $^* p < 0.05$, $^{**} p < 0.01$, $^{***} p < 0.001$

Note: White's robust standard errors in parentheses. The table presents the regression results from the LPM in the period 1996 - 2005.

6.1.2 Time period 2008 - 2015

Table 4 displays the results from the LPM regressions in the time period 2008 - 2015. The basic model (1) shows that a one unit increase in the robot density is associated with a 0.13 percentage points decrease in the probability of being employed. The result is significant at a 10 percent level. Controlling for individual characteristics, yearly effects, and exposure to import competition, the result from model (4), shows that there is no correlation between increased robotization and the probability of employment. However, increased foreign competition is associated with reducing the employment probability. Thus, competition, rather than robotization, is related to employment probability in this period. Skilled workers are associated with significantly benefiting from increased robotization.

Table 4: Dependent variable: Probability of being employed in the time period 2008 - 2015

	(1)	(2)	(3)	(4)	(5)	(6)
Robotization	-0.0013^{+}	-0.0011^{+}	-0.0010	-0.0005	-0.0020*	-0.0014
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0009)	(0.0009)
Robotization × Skill					0.0023^{+}	0.0022^{+}
					(0.0012)	(0.0012)
Age		0.0211***	0.0213***	0.0212***	0.0214***	0.0213***
		(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0020)
Age^2		-0.0002***	-0.0002***	-0.0002***	-0.0003***	-0.0003***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Female		-0.0107	-0.00967	-0.0101	-0.00967	-0.0101
		(0.0067)	(0.0067)	(0.0067)	(0.0067)	(0.0067)
Education		0.0041**	0.0040**	0.0038**	0.0000	-0.0002
		(0.0014)	(0.0014)	(0.0014)	(0.0017)	(0.0017)
Competition				-0.0185*		-0.0187*
				(0.0091)		(0.0091)
Skill					0.0097	0.0102
					(0.0082)	(0.0082)
Constant	0.9680***	0.5360***	0.5310***	0.5410***	0.5380***	0.5480***
	(0.0042)	(0.0431)	(0.0434)	(0.0432)	(0.0433)	(0.0432)
Yearly effects			✓	✓	✓	✓
Observations	5796	5771	5771	5771	5771	5771

$^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: White's robust standard errors in parentheses. The table presents the regression results from the LPM in the period 2008 - 2015.

As shown in model (6), the coefficient on the interaction term between robotization and skill is associated with a 0.2 percentage points higher probability of employment, given a one unit increase in robot density. There is no relationship between increased robotization and employment for unskilled workers. The correlation between increased exposure to import competition and employment is sustained from model (4), and thus, continue to be associated with a negative impact. We note that without controlling for exposure to import competition, in model (5), increased robotization is associated with reducing the probability of employment for unskilled workers, and increase the probability for skilled. Since there are no statistically significant relationships between increased robotization and employment probability, this indicate that technological unemployment is not present in this period. Controlling for exposure to import competition, we do not find that there exists a negative relationship for unskilled workers. The statistically significant effects aside, the relationships are of little economic significance.

6.2 Robustness of the LPM Analysis

As discussed in Sections 4 and 5, the data we use have weaknesses that may impair the results from the LPM analyses. We have chosen the variables which affect the probability of being employed to reduce the omitted variable bias. Hence, we have considered several variables to include in the models. We would preferably have controlled for region specific effects. However, the Norwegian Labor Force Survey only provided a municipality structure connected to each individual. We tried to control for the municipality structure, however, we found no statistically significant relationship to the probability of being employed. Further, we considered a linear trend and GDP instead of year dummies. Although the linear trend and GDP were significantly related to the probability of being employed, they did not alter the coefficients of interest compared to the year dummies. Therefore, we decided to use yearly dummies to control for yearly effects. Including industry-specific dummies was not included due to multicollinearity. We tried to include capital and capital density without finding any statistically relationship to the probability of being employed. To reduce the omitted variable bias, we argue that we have included all the influential observable effects in our analysis.

To evaluate the robustness of our model, we have included robustness analyses to account for the problems that may weaken the LPM analyses. One potential problem is that the relationship between being unemployed and employed may not be linear, and the LPM would generate predictions outside the interval between zero and one. In a binary model, predictions outside the interval between zero and one are not realistic, and indicate that a linear model may not be the best to describe the relationship[5]. Hence, we include a probit model, restricting all the

[5] See Wooldridge (2012) for a description of problems related to predictions outside the interval 0 to 1.

estimated probabilities to be within the interval between zero and one.

A second potential problem is the endogeneity related to reverse causality between robotization and the probability of being employed. In our analysis, we argue that robotization will affect the probability of being employed, however, we cannot exclude the possibility that the relationship may be the opposite. If the probability of being employed causes changes in robotization, we have an endogeneity problem in our model. To avoid this problem, we use an instrumental variables approach (IV). We exploit data on operational robots from the International Federation of Robotics, in combination with data on manufacturing employment from the EU KLEMS database to produce robot densities for Sweden and Germany. By using equally weighted robot densities from subindustries in Sweden and Germany, we can instrument the robot density in Norway, excluding the possibility of Norwegian robotization being affected by the probability of being employed. We emphasize that we have excluded the *Automotives and vehicles* industry from the instrument. According to the International Federation of Robotics, the *Automotives and vehicles* industry is one of the most robot intensive industries (International Federation of Robotics, 2014). Since the Norwegian automotive industry constitute a smaller part of manufacturing compared to Sweden and Germany, we find the instrument to be better after excluding this industry, which are confirmed by higher statistically significant first stages (Germany Trade and Invest, 2016; Norway Exports, 2008; The Scandinavian Automotive Supplier Association, 2017). To be able to exploit employment statistics from EU KLEMS, we had to assume that the worker composition in the manufacturing industries in Sweden and Germany was similar to Norway. We did this to obtain employment statistics for some industries, which only included statistics at a rougher level.

A third potential problem is the definition of who is unemployed applied in the basic LPM model. A surveyed individual is considered as unemployed if it on average has been unemployed in a given year. Thus, individuals who have been temporarily employed, say in one quarter, are not considered unemployed. As seen in Table 1 in Section 5, the unemployment rate from our sample is in general below the registered unemployment rate, and hence, the relationship between robotization and the probability of being employed may be underestimated by not including temporary unemployment. By including temporary unemployment, and redefining education, we estimate the LPM II model, to see whether the results change. We assume that each individual has the same educational level as the previous or next quarter, in case of no response in a given quarter to obtain more observations. In the robustness analyses, we use models (4) and (6) exclusively.

Tables 5 and 6 present the results from the LPM analyses together with the results from the robustness analyses for models (4) and (6) in the time period 1996 - 2005. The positive relationship we find between robotization and the probability of being employed, is statistically insignificant in all of the robustness models in Table 5. Interestingly, in the LPM II, the negative association between the probability of being employed and competition is statistically significant at a 1 percent level. Further, the marginal effect of robotization in the probit model, displays the same coefficient as the original LPM. The IV estimation suggest the same relationship as the other models.

Table 5: Robustness: Model (4) time period 1996-2005

	LPM	Probit	IV	LPM II
Robotization	0.0011*	0.0160	0.0005	0.0008
	(0.0005)	(0.0110)	(0.0010)	(0.0008)
Marginal effect		[0.0011]		
Competiton	-0.0056	-0.0953	-0.0065	-0.0327**
	(0.0070)	(0.100)	(0.0086)	(0.0104)
Yearly effects	✓	✓	✓	✓
Observations	7530	6096	5684	7694

$^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: White's robust standard errors in parentheses. The table presents the results from the robustness analyses. The dependent variable is the probability of being employed. The LPM coefficients are the same as presented in Column (4) in Table 3. The control variables *Age*, *Age*^{2}, and *Education* are included in the analyses, but left out of the table.

In Table 6, the IV-model shows a significant relationship between increased robotization and the probability of being employed in favor of skilled and disfavor of unskilled workers. This finding is consistent with skill-biased technological change. None of the other alternative empirical models display significant relationships consistent with skill-biases. The results are ambiguous, where the IV-model clearly indicate that skilled workers are favored over unskilled in light of increased robotization.

Table 6: Robustness: Model (6) time period 1996-2005

	LPM	Probit	IV	LPM II
Robotization	0.0003	0.0005	-0.0034^{+}	-0.0006
	(0.001000)	(0.0172)	(0.0019)	(0.00158)
Marginal effect		[0.0000]		
Robotization × Skill	0.0011	0.0230	0.0056**	0.0020
	(0.0012)	(0.0222)	(0.0025)	(0.0019)
Marginal effect		[0.0016]		
Competition	-0.0057	-0.0899	-0.0067	-0.0330**
	(0.0070)	(0.1000)	(0.0086)	(0.0105)
Yearly effects	✓	✓	✓	✓
Observations	7530	6096	5684	7694

$^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: White's robust standard errors in parentheses. The table presents the results from the robustness analyses. The dependent variable is the probability of being employed. The LPM coefficients are the same as presented in Column (6) in Table 3. The control variables *Age*, Age^2, and *Education* are included in the analyses, but left out of the table.

Tables 7 and 8 present the results from the robustness analyses of models (4) and (6), respectively, in the period 2008 - 2015. In Table 7, we do not find any statistically significant relationships between robotization and the probability of being employed. As observed in Table 5, the marginal effect of robotization in the probit model is almost identical to the robotization effect in the original LPM. This supports a linear relationship between robotization and the probability of being employed. In Table 8, the probit model finds the relationship between robotization and the probability of being employed for unskilled workers to be statistically significant at a 10 percent level. We find the relationships in the probit and originial LPM to be close to each other, and are not far from showing a significant relationship between robotization and the probability of being employed for unskilled and skilled workers. The same is true for the IV-model, where the relationship between robotization and employment for skilled workers is close to statistically significant at a 10 percent level. As we anticipated, exposure to import competition explains most of the variation.

Table 7: Robustness: Model (4) time period 2008-2015

	LPM	Probit	IV	LPM II
Robotization	-0.0005	-0.0093	-0.0002	-0.0004
	(0.0006)	(0.0085)	(0.0009)	(0.0010)
Marginal effect		[-0.0007]		
Competition	-0.0185*	-0.1760+	-0.0186+	-0.0194
	(0.0091)	(0.0944)	(0.0095)	(0.0118)
Year effects	✓	✓	✓	✓
Observations	5771	5771	4538	5919

$^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: White's robust standard errors in parentheses. The table presents the results from the robustness analyses. The dependent variable is the probability of being employed. The LPM coefficients are the same as presented in Column (4) in Table 4. The control variables Age, Age^2, and $Education$ are included in the analyses, but left out of the table.

We cannot exclude the existence of non-linear relationships, however, the marginal effects and the LPM coefficients are similar, and thus, the linear and non-linear relationships between robotization and the probability of being employed are close. The IV-models are consistent with the other models, both the LPM and the robustness models. Indeed, in the period 1996 - 2005, the IV-model shows a relationship between robotization and employment probability that indicate the presence of skill-biases as a consequence of technological change. We argue that the IV-instruments are appropriate to describe the robotization development in Norway. To decrease the impact of attrition in the sample and increase the sample size, we changed the definition of unemployment and education. Noticeably, this has a significant impact on the relationship between the probability of being employed and exposure to import competition, which corresponds to evidence from previous studies (see e.g. Autor et al., 2013; Balsvik et al., 2015). The robustness analyses do not change the lack of economically significant relationships between robotization and the probability of being employed.

Table 8: Robustness: Model (6) time period 2008-2015

	LPM	Probit	IV	LPM II
Robotization	-0.0014	-0.0169^{+}	-0.0016	-0.0008
	(0.0009)	(0.0010)	(0.0013)	(0.0013)
Marginal effect		[-0.0012]		
Robotization × Skill	0.0022^{+}	0.0272	0.0035	0.0009
	(0.0012)	(0.0193)	(0.0021)	(0.0018)
Marginal effect		[0.0019]		
Competition	-0.0187*	-0.1840^{+}	-0.0189**	-0.0199^{+}
	(0.0091)	(0.0954)	(0.0146)	(0.0118)
Year effects	✓	✓	✓	✓
Observations	5771	5771	4538	5919

$^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: White's robust standard errors in parentheses. The table presents the results from the robustness analyses. The dependent variable is the probability of being employed. The LPM coefficients are the same as presented in Column (6) in Table 4. The control variables *Age*, Age^2, and *Education* are included in the analyses, but left out of the table.

Acemoglu and Restrepo (2017) address that robotization has to be distinct, and weakly correlated with imports, the decline of routine jobs, off-shoring, IT-technology, and capital in Europe, in order to investigate the effect of robotization. This is because the adoption of robots can be concurrent with changes in these industry effects. In Figures 9 and 10, we observe that robotization, and import density and capital density are distinct and weakly correlated. However, other industry trends, such as the decline of routine jobs and growth in IT-capital, that we do not have available data on, may be correlated with robotization. Thus, we cannot completely rule out the possibility of correlation between robotization and other industry effects. Hence, we are not able to entirely isolate the effect of robots on employment probability.

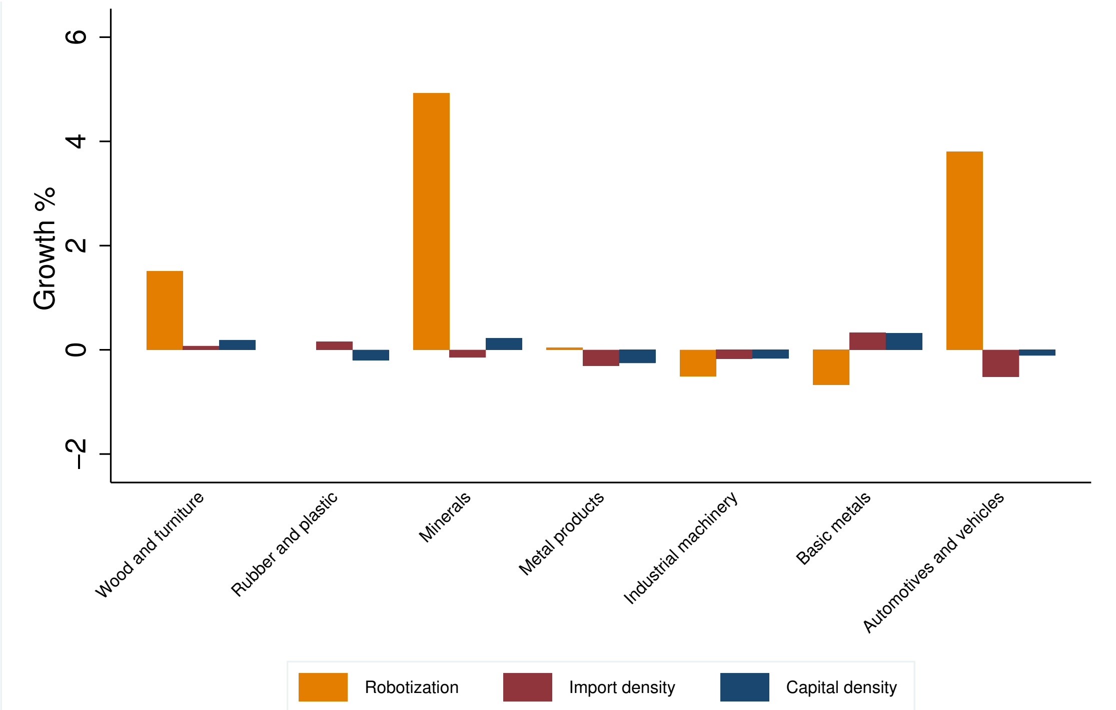

Figure 9: Growth in robotization, import, and capital 1996 - 2005

Note: This figure plots the growth in the number of robots per 1,000 workers, robotization, import per 1,000 workers, import density, and capital per 1,000 workers, capital density, in the period 1996 - 2005 for the 7 IFR industries we have included in our sample. The data on workers, imports, and capital in the industries is obtained from SSB.

In the time period 1996-2005, Figure 9 shows that the growth in robot densities is ambiguous. Further, the capital density is stable, while the import density is ambiguous across the industries. Figure 10 shows the densities in the time period 2008-2015. The growth in robot density is more moderate. Notably, in the industries *Minerals* and *Metal products* the robot densities decrease. Most of the industries were experiencing higher import density compared to the previous, which is consistent with the results from our analysis. All of the industries have experienced a decrease in capital density. The figures show that most of the industries that are adopting more industrial robots, are not necessarily the same industries affected by foreign competition. We conclude that robotization is not associated with import density and capital density. This development is consistent with what Acemoglu and Restrepo (2017) find for EU countries.

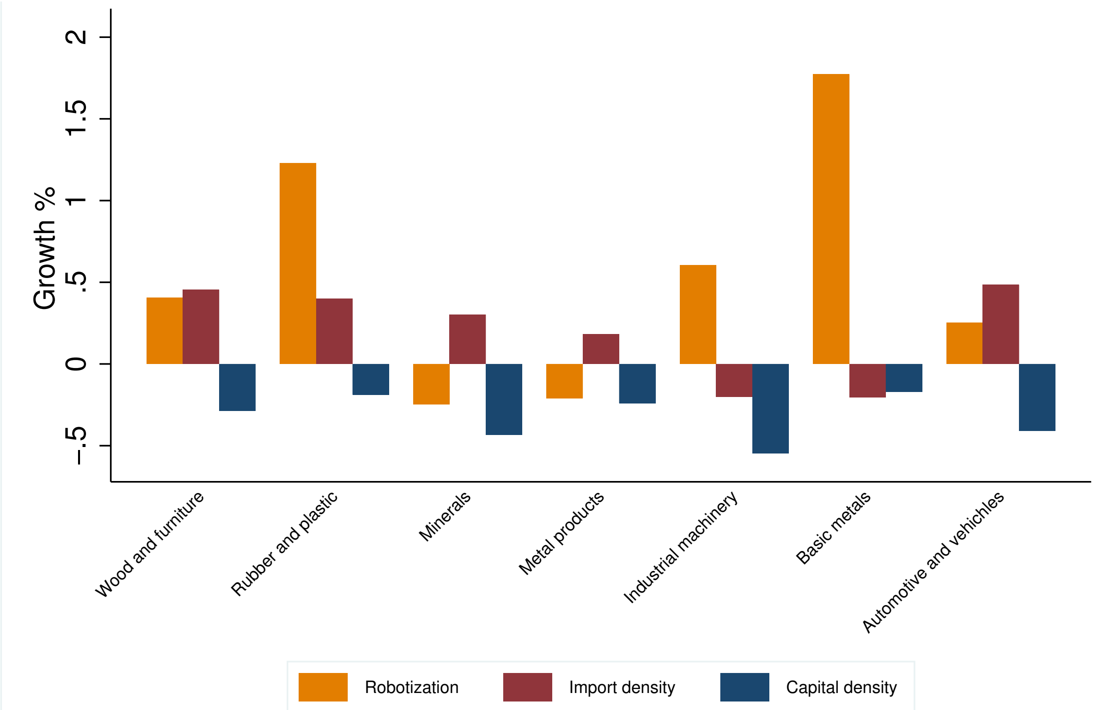

Figure 10: Growth in robotization, import, and capital 2008 - 2015

Note: This figure plots the growth in the number of robots per 1,000 workers, robotization, import per 1,000 workers, import density, and capital per 1,000 workers, capital density, in the period 2008 - 2015 for the 7 IFR industries we have included in our sample. The data on workers, imports, and capital in the industries is obtained from SSB.

7 Discussion

According to a report from the Norwegian Board of Technology, increased automation both creates opportunities and imposes challenges on Norwegian manufacturing industries (Norwegian Board of Technology, 2013). Increased automation of manufacturing processes, that has become evident over the past couple of decades, may be well-suited for a small open economy with high levels of digital competence and high wage costs. However, increased automation, and new opportunities for Norwegian manufacturing industries, does not necessarily imply that the current level of employment will be sustained, or that future demand for skills will be equal to present demand.

The descriptive analysis of robots in Norway, presented in Section 4, suggest that Norway differs from the European comparisons Sweden and Germany in developments of operational industrial robots, manufacturing employment, and hence, robot density. In Norway, robotization has been lower compared to Sweden and Germany. The differences between the three countries may originate from differences in the industry structures. According to the International Federation of Robotics, the automotive industry is the most important customer of industrial robots, and thus, has emerged as the most important driver of the recent growth in industrial robots (International Federation of Robotics, 2014). Since 2010, the automotive industry has considerably increased investments in robots worldwide. In both Sweden and Germany, the automotive industry constitute a substantial part of the manufacturing industry. Germany is the number one automotive manufacturer in Europe, and the industry is the largest both in terms of revenue and employment. In 2015, German automobile manufacturers produced more than 15 Million vehicles, equivalent to more than 19 percent of total global production (Germany Trade and Invest, 2016). In Sweden, the annual exports from the automotive industry amount to 12 percent of total exports, and has both leading vehicle producers in manufacturing and development, in addition to more that 300 subcontractors (The Scandinavian Automotive Supplier Association, 2017). Contrary to the Swedish and German automotive industries, the Norwegian counterpart is, to a larger extent, dominated by automotive supplier companies. By specializing in niche areas of automotive parts, Norwegian subcontractors provide parts to automotive industries in the world (Norway Exports, 2008). The differences in the importance of the automotive industry, can explain why Norway differs from Sweden and Germany in the number of operational industrial robots.

Graetz and Michaels (2017) do not find significant effects of increased robotization on employment in the EU. Their findings suggest that although increased automation has the possibility to make labor redundant, such a development is not evident yet. Autor et al. (2013) for the US and Balsvik et al. (2015) for Norway, suggest that negative changes in the employment share of manufacturing industries can be attributed to increased exposure to Chinese imports. In our analysis of a subsample of Norwegian manufacturing industries, we find no relationship consistent with technological unemployment. Between 1996 and 2005, increased robotization is associated with an increase in the probability of being employed. One possible explanation why the coefficient is positive, is that increased robot density boosted Norwegian manufacturing industry in international competition. Another explanation may be that the robots in this time period required a certain level of human assistance. Hence, increased robotization implies a higher level of labor, and thus is associated with positive effect on the probability of employment. We find no relationship between increased robotization and employment probability in the 2008 - 2015 period, but increased import competition is associated with a negative impact on employment. This can be explained by the growth of low-cost countries in the 1990s and 2000s, and a following outsourcing of production by manufacturing companies to reduce costs. Thus, our results are consistent with previous research from other countries, indicating that increased robotization in Norwegian manufacturing industries is not associated with negative employment outcomes in both periods, but employment is negatively correlated with increases in import exposure in the 2008 - 2015 period.

The opportunities created by increased robotization may strengthen Norwegian manufacturing industries in international competition. In the light of robotization, the advantages of offshoring production have become smaller, and Norwegian manufacturing companies have started to move production home from low-cost countries, known as “homeshoring” (Aale, 2013; Iversen, 2017; Norwegian Board of Technology, 2013; Stensvold, 2016). However, by locating production in the domestic market, cost efficiency is still important. This may intensify competition, which further can contribute to stimulate increased innovation in the industries. Innovation can expand the industrial possibilities, developing new products, and create new industries and new jobs. This can explain why we do not see negative relationships between increased robotization and employment. International competition has been a larger threat to manufacturing workers than robotization, and increased robotization may reduce the manufacturing employment consequences of increased competition.

Graetz and Michaels (2017) stress that, although they find no effect of increased robotization on employment, the results suggest a change in the composition of the work force. The compositional change favors skilled workers over unskilled workers, and is consistent with skill-biased technological change. In the period 1996 - 2005, our results show no association between being skilled and having advantages in the labor market compared to unskilled workers in the LPM analysis. However, the IV-model shows that there is a positive relationship between robotization and employment for skilled workers, and a corresponding negative relationship for unskilled workers. The IV-results indicate that skill-biases may occur. In the time period 2008 - 2015, skilled individuals are associated with being positively affected by increased robotization in the LPM, and are close to significant in the IV-model. One possible explanation of the positive correlation for skilled workers, is that robots have become more sophisticated, and hence, a higher skill level is required to monitor and control the robots.

According to the Norwegian Board of Technology (2013), newer industrial robots have become increasingly sophisticated in terms of production speed, flexibility, and precision. The newer generations of industrial robots are better equipped with sensors, increasing their safety and hence, convenience in work alongside of humans. These new robots represent a change in the use of robots, that implies a change in the skills required. Our results for Norway are consistent with what Graetz and Michaels (2017) found for EU countries, and show that skill level is associated with inflicting changes on the composition of the workforce in the period 1996 - 2005. Although increased robotization is positively associated with employment for skilled workers in the 2008 - 2015 period, there is no association between unskilled workers and increased robotization. One reason may be that, although skilled workers may have had an advantage because of the evolution of robots, increased robotization have not altered the labor market dynamics substantially. The results from the robustness analyses do not deviate from the results provided by the LPM analysis. One interesting feature in the robustness analysis LPM II, is that we capture temporary employment. However, including temporarily employed do not change the results from the basic LPM analysis, and we stress that none of our results are of economic significance.

In spite of the obvious advantages robotization have on domestic industry production, increased robotization impose challenges on Norwegian manufacturing industries. Although increased use of industrial robots will not eliminate human labor from production processes, they will alter the needs for hours worked and the type of expertise required. Thus, the developments in production technology induce changes in the skill level of workers. New technologies increase the demand for skilled workers able to program, monitor and control the robots, and reduce the demand for typically unskilled operators. In this respect, skill-biases are likely to occur. In our analysis, neither the LPM analysis nor the probit analysis display concrete evidence of skill-biased technological change. Although the relationships we find are insignificant, the results from the 2008-2015 period suggest that increased robotization is in favor of skilled workers. New jobs are created from new technology, however, the new jobs require new types of skills. As it takes time to build skills, the gap between the current level of skill and the required level might increase, inducing skill-biases. Hence, we might experience skill-biases during a transition period in the short-run. In the long-run, however, the differences in demand and supply of required skill are likely to level out, as workers acquire new skills.

The results we have found do not share John M. Keynes' concerns from the 1930s, and humans seem to be able to race *with* the machines. Thus, man remains useful in performing certain tasks, and labor is still important. The phenomenon of "Polanyi's paradox" may be an explanation of the results apparent. The paradox, in essence, states that the tacit knowledge of how the world works often exceeds the explicit understanding we have. Transferred to the connection between robotization and employment, the main takeaway is that, although robots can be highly sophisticated in the tasks they perform, humans will remain superior in certain tasks that require flexibility, judgment, and common sense (Autor, 2014). A robot can be taught to produce car parts and assemble them, but only a human can judge whether the car is comfortable to drive.

8 Conclusion

The main purpose of this thesis has been to shed light on whether there exists relationships between increased robotization and the probability of being employed in Norwegian manufacturing industries in the two time periods 1996 - 2005 and 2008 - 2015. Increased robotization has been, and will continue to be a topic of discussion due to possible consequences on labor.

We utilize data on operational industrial robots from the International Federation of Robotics, and data on individuals connected to Norwegian manufacturing industries from the Norwegian Labour Force Survey. Thus, we exploit the variation in robotization between different subindustries. The degree of robotization is measured as robot density, the number of robots in an industry divided by the employment in that industy. To capture the relationship between robotization and employment probability, we use linear probability models, and include non-linear models, an IV estimation, and a widened measure of employment in a robustness analysis.

The results from the LPM analyses, show that there are no negative associations between increased robotization and the probability of being employed. Indeed, in the 1996 - 2005 period, we find a positive association between increased robotization and employment probability. Further, we find no negative relationship between increased robotization and being unskilled, although, in the 2008 - 2015 period, being skilled is associated with a positive employment probability given increased robotization. Including the robustness analyses, the results do not persist, indicating that although the LPM analysis seems to be fitting, it may overestimate some of the relationships and underestimate others. The IV-analysis in the period 1996 - 2005, indicate that skill-biased technological change may occur in this period. The results are, however, of little economic significance, as a one unit change in robot density is large in a Norwegian context.

Our results imply that increased robotization over the past 20 years, is not associated with negative total employment outcomes in Norwegian manufacturing industries. Whether these results will be valid in the next 20 years is difficult to predict, however, robots will continue to both create opportunities and impose challenges in Norwegian manufacturing industries.

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A Appendix

Table A1: Correspondence between the ISIC and the International Federation of Robotics (IFR) classifications of industries

Code	ISIC rev. 3/3.1	Code	ISIC rev. 4	Code	IFR	Sample
20	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials.	16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials.	16	Wood and furniture	Wood and furniture
36	Manufacture of furniture; manufacturing n.e.c.	31	Manufacture of furniture			
23	Manufacture of coke, refined petroleum products and nuclear fuel	23	Manufacture of other non-metallic mineral products	23	Glass, ceramics, stone, mineral products (non-auto)	Minerals
25	Manufacture of rubber and plastics products	22	Manufacture of rubber and plastics products	22	Manufacture of rubber and plastics products without automotive parts	Rubber and plastic
				2932	Rubber and plastic parts and accessories for motor vehicles	
27	Manufacture of basic metals	24	Manufacture of basic metals	24	Basic metals	Basic metals
28	Manufacture of fabricated metal products, except machinery and equipment	25	Manufacture of fabricated metal products, except machinery and equipment	25	Metal products	Metal products
29	Manufacture of machinery and equipment n.e.c.	28	Manufacture of machinery and equipment n.e.c.	28	Industrial machinery	Industrial machinery
34	Manufacture of motor vehicles, trailers and semi-trailers.	29	Manufacture of motor vehicles, trailers and semi-trailers.	29	Automotive	Automotives and vehicles*
35	Manufacture of other transport equipment.	30	Manufacture of other transport equipment.	30	Other vehicles	

Note: n.e.c = not elsewhere classified. *Automotives and vehicles are aggregated to be able to control for import competition in both time periods.