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ABSTRACT

How Robots Change Within-Firm Wage Inequality*

Using novel matched employer-employee register data with firm-level information on the introduction of industrial robots, this paper analysis the impact of robots on the wages of workers in the manufacturing sector. The results show that industrial robots increase wages for high-skilled workers relative to low-skilled workers, hence robots increases the skill-premium within firms. Furthermore, we find that employees in managerial positions benefit more from robotisation than those in STEM or professional occupations. Overall, our results suggest that the introduction of industrial robots has a positive effect on the average wages of manufacturing workers in Norway.

JEL Classification: J01, J08, O33, E24

Keywords: automation, robotisation, labour economics, wages, technological change

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1. Introduction

As firms have increased their use of robot technology in the production process, the interest of understanding their impacts on labour markets has increased. In the last decades it has been documented that advanced machines and robots have started to undertake tasks that were previously undertaken by humans (Frey and Osborne 2017, Brynjolfsson and Mitchell, 2017), potentially resulting in decreasing earnings and lower employment (Acemoglu and Restrepro, 2019). Experts expect this trend to accelerate in the coming years. Robot technologies are advancing at a rapid pace with prices of new robots estimated to decrease by 20% and performance to improve by 5 % annually (Boston consulting Group (2015). This fast pace of progress in technology has raised the prominence of the question: how will robotisation affect workers?

During previous periods of large technological changes, economies have managed to increase the demand for new types of jobs, resulting in increased overall employment (Autor, 2015), but some worry that the recent development in robot technology represent something fundamentally new, potentially posing a stronger and more permanent threat to wages and employment (see e.g., Brynjolfsson and McAfee, 2014). Others argue that the technological development we observe now may not be so different from previous ones. Perhaps while some jobs will be lost, the demand for other jobs, that are complements to the new technologies, will increase (Autor and Solomons, 2017).

A key question is how the introduction of robot technologies affect the demand for different types of workers. Historically, we have seen periods of skill-biased technical change (Katz and Murphy, 1992), with increasing demand for high-skilled workers and declining demand for low-skilled workers, and periods of polarization in the labour market with increasing employment at both the bottom and the top of the occupational earnings distribution and declining employment in the middle of the occupational earnings distribution (Autor, Katz and Kearney, 2006). We answer the above question by studying how the introduction of robot technology affects wage differences between workers with different levels of education within the firms, and how the introduction of robot technology affects wage differences between workers in different occupations within the firms.

There is not much empirical micro-level evidence on the impacts of these new robot technologies on the wages of workers. This lack of evidence is largely explained by the lack of appropriate data, especially linked employer-employee data, containing firm-level information on robot use (for a discussion of this shortcoming, see Barbieri et al. 2019). Only a handful of recent papers from 2020 and late 2019 utilise firm-level robotisation data.[1] This paper contributes with micro-level evidence on the impacts of robots on wages, for both individuals and firms. We use Norwegian matched employer-employee data with precise firm-level information on robot investments. We exploit the fact that the vast majority of industrial robots used in Norway are imported from abroad, and not produced in Norway. Therefore, we use trade statistics data, containing information on the imports of industrial robots, linked to firms, to analyse the impact of robots on both individuals and firms. The panel dimension of our data also allows us to investigate the relative wage effects for various groups within firms, defined by education level and occupation type over time. The period of analyses is 1999-2016.

Our results show that robot introduction has a positive effect on average wages. To identify differences in wage effects across workers with different levels of education and in different occupations, we utilize an empirical framework including both job-spell fixed effects and time varying firm effects.[2] When we look at the relative wage effects for various groups of workers, we find that workers with higher education benefit the most, while workers with the lowest level of education benefit the least. Our results for different occupation categories reveal

[1] Recent papers by Humlum (2019), Acemoglu et.al. (2020), Bessen et al (2020) and Dixon et al (2019) are discussed in the literature section below.

[2] See Lachowska et al (2020), Engbom and Moser (2020) and Barth et al (2020).

that managers experience the highest wage increase following the introduction of robot technologies, employees in STEM occupations follow with more moderate gains, followed again by other professionals. Blue-collar and other non-professional occupations gain the least from the introduction of robot technologies.

The rest of the paper proceeds as follows. The next section gives a brief presentation of previous literature. Section 3 presents the theoretical framework, and section 4 presents the empirical specifications. Section 5 presents the data, the sample and the variables. Section 6 presents the results, while section 7 concludes.

2. Related literature

In the last few years there has been a growing literature looking at the impact of robotisation on labour market outcomes like wages and employment (Acemolglu and Restrepo, 2019, Graetz and Michaels, 2018).[3] These studies are almost all based on industry level data with the majority using data from the International Federation of Robotics (IFR) in order to identify the penetration of robots at the industry level. Acemolglu and Restrepo (2019) analyse the effect of the increase in the use of industrial robots 1990-2007 on US wages and employment. The local labour market impacts of robots is estimated by regressing the change in employment and wages on the exposure to robots in each local labour market, defined from advances in robotics technology in each industry and the local distribution of employment across industries. Using this approach, they estimate significant negative effects of robots on employment and wages across commuting zones. Graetz and Michaels (2018) analyse the economic contributions of industrial robots using a panel data set on robot adoption within industries in 17 countries in the period 1993-2007. Their findings suggest that increased robot use contributed positively to

3 Barbieri et.al. (2019) provides a recent review of the literature on the employment impacts of automation, robots and artificial intelligence.

annual labour productivity growth and total factor productivity. Their results suggest that robots did not significantly reduce total employment, but they reduced the employment share of low-skilled workers.

Dauth et al. (2018) present evidence from Germany on the impacts of robots, in the period 1994-2018. They find that the adoption of industrial robots had no effect on total employment in local labour markets specializing in industries with high robot usage. Furthermore, they find that robot adoption has not increased the risk of displacement for incumbent manufacturing workers. Their results on wages suggest a small and insignificant impact on wage growth in total. Furthermore, the article finds negative effects within manufacturing and positive effects in the service sector.

Chiacchio et.al. (2018) study the impact of industrial robots on employment and wages in six European Union countries. They adopt the local labour market equilibrium approach developed by Acemoglu and Restrepo (2019). They find that one additional robot per thousand workers reduces the employment rate by 0.16-0.20 percentage points. They find that the displacement effect is particularly evident for workers in the middle of the education distribution, for young cohorts, and for male workers. Their results, however, do not point to any significant results on the impact of robots on wage growth.

With respect to employment, the results are mixed. While some studies find no significant effect of robots on total employment (Graetz and Michaels, 2018; Dauth et.al. 2017), others find a statistically significant negative effect (Acemoglu and Restrepo, 2019; Chiacchio et.al, 2018). With respect to wages, results are mixed, reporting both negative effects (Acemoglu and Restrepo 2019) and no effects (Chiacchio et.al 2018), and results show different effects for different industries (Dauth et al. 2018).

Common for all of the above studies is that they use data on robot use on industry or the combination of industry and region. There are a limited number of studies that present empirical evidence on actual firm-level usage of robots, and even fewer with linked firm and individual level data, largely due to the lack of microdata measuring robot adoption at the firm level (Barbieri et.al. 2019). Information on robot use at the industry and geographic region level is insufficient to reveal the mechanisms through which firms are using robots in the production process, and how the firms introduction of robots are related to their employment and earnings. To do that firm-level information on robot use is necessary.

Only a few studies have used firm-level information on robot use in their analyses of the impacts of industrial robots (Humlum, 2019, and Dixon et al., 2020). Humlum (2019) uses a Danish matched employer-employee data for the period 1995-2015, with linked firm-level robot information, to study the impact of industrial robots. First, using event studies, he finds that firms expand output, lay off production workers, and hire tech workers when they adopt industrial robots. Secondly, employing a dynamic general equilibrium framework that takes into account the ability of workers to reallocate across occupations in response to robots, he finds that industrial robots have increased average real wages by 0.8 percent but have lowered real wages of production workers employed in manufacturing by 6 percent. Dixon et al (2020) use Canadian firm-level data for the period 1996 to 2017. They show that investments in robotics are associated with increased employee turnover, but also an increase in total employment within the firm.

Acemoglu et al (2020) use firm-level data from France between 2010 and 2015 and finds that overall employment increases faster in firms adopting robots. However, in that study the firms are not linked to individual workers. Finally, Bessen et al (2020) provide firm level evidence on automation from the Netherlands in the period 2000-2016. Using an event study design, they find that firms save labour after investing in automation technology, while wages rise. Similar to Acemoglu et al. (2020), they do not have a link to individual workers.[4]

[4] Two other papers using firm-level data on robots on firm outcomes, include Dinlersoz and Wolf (2018), and Bonfiglioli et al. (2019).

We extend the scant literature analysing the impact of robots on wages in at least two ways. First, we use novel data containing firm-level information on robot use, adding to the limited literature exploiting robot information at the firm level. Second, we use an econometric approach that accounts for time varying firm effects, that is well suited to analyse the relative impact of robots on different groups of workers.

3. Theoretical framework

Robots in production

We build a simple framework inspired by the model in Graetz and Michaels (2018), but adapted to firm-level robot adoption, as in Humlum (2019), and to a situation with tasks that may be undertaken by workers of different skills. Consider the following production function:

$$Q = A(\alpha_H {Y_H}^{\rho} + \alpha_L {Y_L}^{\rho})^{\frac{1}{\rho}}$$

Where Y_i is tasks measured in units of labor, and $\rho \varepsilon(-\infty,1)$. Let $L = L_H + L_L$ be labour input of skill type H and L (e.g. level of education) into the production of tasks. Y_H are tasks that require skill level H, for example management or engineering tasks, while Y_L are tasks that require skill level L, for example manual tasks. We assume that the H- and L tasks are complements, i.e. $\rho < 0$.

For illustration, we assume that Y_H cannot be substituted by robots, such that $Y_H = L_H$. Furthermore, we divide Y_L into tasks that may be undertaken by robots, Y_{Lr}, as prefect substitutes for labour, and task that require low skill labour input, Y_{Ll}. Let

$$Y_L = (c{Y_{Lr}}^{\lambda} + (1-c){Y_{Ll}}^{\lambda})^{\frac{1}{\lambda}}$$

The r and l tasks undertaken by low skill labour can be either substitutes or complements. However, we assume that $\rho < \lambda$, so that the task undertaken by the same type of labour are more substitutable than tasks undertaken by the two different types of labour[5]. If the firm has implemented robot technology, we follow Greatz and Michaels (2018) and assume that the rental price of robots is sufficiently low to replace labour completely with robots for tasks Lr, and for robot-using firms we thus have;

$$Y_L = (cR^{\lambda} + (1-c){L_L}^{\lambda})^{\frac{1}{\lambda}}$$

Whereas firms that rely on manual technology have: $Y_L = L_L$, and thus $Q = A(\alpha_H {L_H}^{\rho} + \alpha_L {L_L}^{\rho})^{\frac{1}{\rho}}$.

Inserting labour and robots for tasks in the robot-using firms gives Q(L_L, L_H, R). The marginal productivity of labour may be written:

$$\frac{\delta Q}{\delta L_H} = \left(\frac{Q}{L}\right)^{1-\rho} \left(\frac{L_H}{L}\right)^{\rho-1} \alpha_H$$

$$\frac{\delta Q}{\delta L_L} = \left(\frac{Q}{L}\right)^{1-\rho} \left(\frac{L_L}{L}\right)^{\rho-1} \alpha_L \left(\frac{L_L}{Y_L}\right)^{\lambda-\rho} (1-c) = \left(\frac{Q}{L}\right)^{1-\rho} \alpha_L \left(\frac{L_L}{L}\right)^{\rho-1} e^{\delta_L}$$

where $e^{\delta_L} = \left(\frac{L_L}{cR+(1-c)L_L}\right)^{\lambda-\rho} (1-c)$ is a "within-firm, direct robot-depreciation factor" of the marginal productivity for labour of type L in robot firms. It is labelled "within firm" since it is conditional on the overall labour productivity of the firm. It is labelled "direct" since it is conditional on the share of low-wage workers in the firm.

It is labelled a "depreciation factor" since by assumption e^{δ_L} <1 (i.e. $\delta_L < 0$). To see why this is a reasonable assumption, note that a robot using firm will chose to allocate R and L_L according to the following condition: $\frac{R}{L_L} = \left(\frac{wc}{r(1-c)}\right)^{\frac{1}{1-\lambda}}$, where r is the rental price of robots and w the wage rate of L-workers. Since there are costs associated with robot adoption, firms that have adopted robot technology will reasonably face a sufficiently low rental price for robots

[5] The assumptions regarding the parameters are made to provide interpretation and highlight certain reasonable mechanisms, but are estimated freely in the empirical implementation of course.

combined with a sufficiently high share of substitutable task, c, such that $\frac{wc}{r(1-c)} > 1$. Thus if $\frac{L_L}{cR+(1-c)L_L} = \frac{1}{1+c\left[\frac{wc}{r(1-c))}^{\frac{1}{1-\lambda}}-1\right]} < 1$. We have:

$$ln\frac{\delta Q}{\delta L_L} = (1-\rho)ln\left(\frac{Q}{L}\right) + (\rho - 1)ln\left(\frac{L_L}{L}\right) + ln\alpha_L + \delta_L$$

$$ln\frac{\delta Q}{\delta L_H} = (1-\rho)ln\left(\frac{Q}{L}\right) + (\rho - 1)ln\left(\frac{L_H}{L}\right) + ln\alpha_H$$

Wage Setting

We allow for different wages in different firms, and employ a simple monopsony model to determine wages. See e.g. Manning (2003) for a detailed discussion. The labour supply of skill group g facing each firm is given by $L_g(w_g)$, where $\frac{\delta L_g}{\delta w_g} > 0$. Let $\varepsilon_g > 0$ be the elasticity of labour supply facing the firm. Profits are given by:

$$\Pi(\boldsymbol{w}) = Y - \sum w_g L_g - rR = pQ(L_L(\mathrm{w}_L), L_H(\mathrm{w}_H), R) - \sum w_g L_g - rR$$

Where Y=pQ is total revenue and r is the rental cost of robots. Profit maximization w.r.t w_g gives:

(1) $$w_g = p\frac{\delta Q}{\delta L_g}\frac{\varepsilon_g}{1+\varepsilon_g} = p\frac{\delta Q}{\delta L_g}m_g$$

Where m= $\frac{\varepsilon}{1+\varepsilon}$ is the "monopsony discount" on wages.

4. Empirical implementation

The above model will be utilized to obtain the skill-group (g) specific component of the wage in firm j at time t; w_{gjt}. Individual wages are given by $w_{ijt} = e^{\alpha_i + X_{it}b + \xi_{ij}} w_{gjt}$, where $\alpha_i = Z_i b^z + \alpha_g + \tilde{\alpha}_i$ is an individual fixed component, including observables, Z_i, such as gender and type of education, a skill-group component, α_g, is an unobserved individual fixed effect, $\tilde{\alpha}_i$

, and a match specific component between the individual and the firm, ξ_{ij}. We represent the monopsony mark-down for skill-group g at time t in firm j by the decomposition $m_{jt} = e^{m_g + \mu_{jt}}$ where m_g is a group specific term, reflecting differences in supply elasticity across the different types of labour, and μ_{jt} is a time varying component reflecting firm specific components, such as the firm's relative position in the local wage distribution. Combining these expressions with (1) gives:

$$(2) \qquad lnw_{ijt} = \underbrace{\alpha_i + \mathrm{m}_g + \xi_{ij}}_{\psi_{ij}} + \underbrace{\mu_{jt} + p_{jt} + (1-\rho)ln\left(\frac{Q_{jt}}{L_{jt}}\right)}_{\varphi_{jt}} + X_{it}b + (\rho-1)\ln\left(\frac{L_{gjt}}{L_{jt}}\right) + \delta_g R_{jt} + u_{ijt}$$

So that log wages may be expressed as a function of a fixed job-spell effect, ψ_{ij}, time varying firm effects[6], φ_{jt}, time varying individual characteristics, and the skill group's share of employment. Finally, the model includes the direct robot-depreciation factor (δ_g), interacted with the treatment indicator, R_{jt}. The robot indicator, R_{jt}takes the value of one for firms with robot technology at time t and zero otherwise.

The fixed job-spell effect absorbs all the constant characteristics of the individual within the current job: observed and unobserved individual characteristics and the unobserved fixed match effects. The time varying firm effects absorb all time varying firm specific characteristics, such as the monopsony discount, the firm specific demand and productivity shocks, the robot component of average productivity and productivity impact of the relative use of skill group g. The interpretation of these effects depends on the normalization of the time varying firm effects: If we exclude a reference year (t=0), i.e. the first year a firm appears in the panel, from the φ_{jt} vector in the estimation, the job-spell fixed effects, ψ_{ij} absorb the individual

[6] See Lachowska et al (2020), Engbom and Moser (2020) for details on identification of both individual- and time-varying firm effects, and Barth et al (2020) for details on the estimation of within firm differential effects with job-spell fixed effects and time-varying firm effects.

fixed effect, the group effect, the firm effect for the reference year, and the match specific effect: $\psi_{ij} = \alpha_i + \alpha_g + \mathrm{m}_g + \xi_{ij} + \varphi_{j0}$; - and the estimated year specific firm effects will be defined as the difference from the reference year:. $\tilde{\varphi}_{jt} = \varphi_{jt} - \varphi_{j0}$.

The remaining variables represent the time varying components of the wage that varies within the firm. Xb is the time varying individual component. The two last terms, $(\rho - 1)ln\left(\frac{L_g}{L}\right) + \delta_g R_{jt}$ represent the time varying part of the group specific component of labour productivity. It also depends on the use of robots in the firm, where δ_g is identified relative to a reference group, g=0, only.

Estimation procedure: Step 1

Estimating equation (2) provides us with an estimate of δ_g that controls for individual fixed effects, match specific effects, and yearly firm effects, in addition to the other time varying covariates. We note that any unobserved productivity- or mark-down shocks to wages, as well as changes in capital or any efficiency effects arising from group composition, are effectively controlled for. In addition, any effect of robots that affect wages similarly for all workers is controlled for. What we are left with is a remarkably clean measure of the relative impact of robots within firms on any group g≠0, relative to the reference group, g=0.

Estimation procedure: Step 2

Using the estimated δ_g's from step 1, we calculate an estimate of L_{jt} = L* that may be used in step 2. In step 2 we estimate the firm level equation:

$$(3) \qquad \varphi_{jt} = \mu_{jt} + p_{jt} + (1-\rho)ln\left(\frac{Q_{jt}}{L_{jt}}\right) + e_{jt}$$

Where φ_{jt} is obtained from step 1.[7] Note that while the estimation of (2) conditions on unobserved productivity and mark-down, unbiased estimations of (3) requires standard exogeneity assumptions on, K, R and their relative efficiency. We address this question by adding year dummies and fixed firm effects in step 2: $e_{jt} = \gamma_t + e_j + \varepsilon_{jt}$, and assume that ε_{jt} is orthogonal to the r.h.s variables of (3) .

5. Data, sample and variables

We exploit matched employer-employee register data, collected and organised by Statistics Norway. The sample consists of all workers employed in the manufacturing industry in the period 1999-2016. To this sample of workers, we merge individual and firm-level variables.

The key individual level dependent variable is log hourly wage. Hourly wage is constructed from individual information on the total wage sum in the job in a given period, the length of the period (number of working days), and weekly working hours.

The key explanatory variable is firm-level information on the use of robots. Information on robots is based on the firm's import of goods, taken from international trade data. Trade data is collected from the Norwegian Trade Statistics Register. Trade flows are reported according to the 8-digit combined nomenclature. These are aggregated up to the Harmonised system (HS) to be compatible with the COMTRADE data, which is the United Nations International Trade Statistics Database. From this database we include the firm's annual imports of industrial robots (HS-code=84795000), measured both by the numbers and value of imported robots (measured in Norwegian kroner (NOK)). From this information, we construct a dummy variable, taking the value 1 if the firm has robots, and 0 otherwise. The variable takes the value 1 the first year the firm is observed with robots, and also in the subsequent years.

[7] A complication arises from the fact that φ_{j0} is absorbed in the job fixed effect. This is resolved by first using a standard AKM decomposition to separate the person and firm components of the job effect, and next add the estimated φ_{j0}'s to the estimated φ_{jt} from step 1.

Individual level control variables include information on age and educational attainment. We construct four categories of education, based on standard classification of education: higher education (university or college degree), upper secondary education, compulsory school (including primary school and lower secondary), and unknown education.

Occupational groups are defined using the International Standard of Occupational Codes 2008 (ISCO-08). We define five groups: i) *Managers*: First digit of ISCO-08 = 1, ii) *Stem professionals*: ISCO-08=21 (Science and engineering professionals) and ISCO-08=31 (Science and engineering associate professionals), iii) *Professionals other*: ISCO-08=2 (Professionals) excluding Stem=21 and ISCO-08=3 (Technicians and associate professionals) excluding Stem=31, iv) *Blue-collar workers:* ISCO-08 code 7 and 8 (<83), and v) *Other non-professionals:* the remaining ISCO-08 code > 3.

Finally, firm-level controls include measures of firm employment, capital per worker, and value added per worker, all measured in logs.

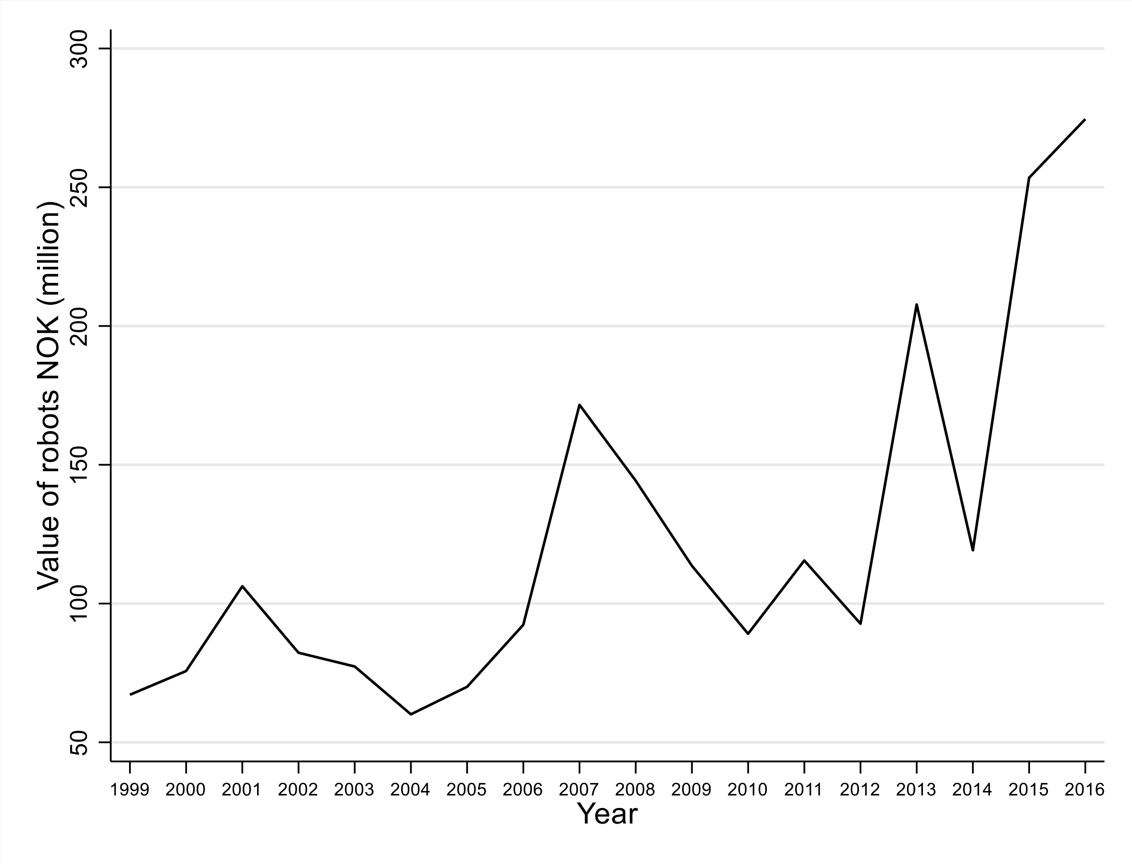
Industial Robots in Norway

There has been a significant rise in the number and total value of industrial robots imported to Norway in our sample period. While in 1999 Norway imported robots worth just over 70 million Norwegian kroner, the figure for 2016 was over 270 million kroner (see Figure 1). Given that the lifespan of robots is estimated to be somewhere between 5 and 12 years depending on application, this amounts to a significant stock of robots for a country with a relatively small manufacturing sector.

Figure 1 shows that similar to trends in other countries the global recession around the year 2008 reduced the total value of new robot imports for a few years after imports of robots picked up again after 2012.

A similar trend can be observed when looking at the number of individual robots imported, dotted line in Figure 2. The number of robots imported increased from around 100 in 1999 to just under 300 in 2016. Figure 2 also shows the same temporary reduction in yearly imports around the year 2007, along with the strong increase in yearly imports between 2012 and 2015.

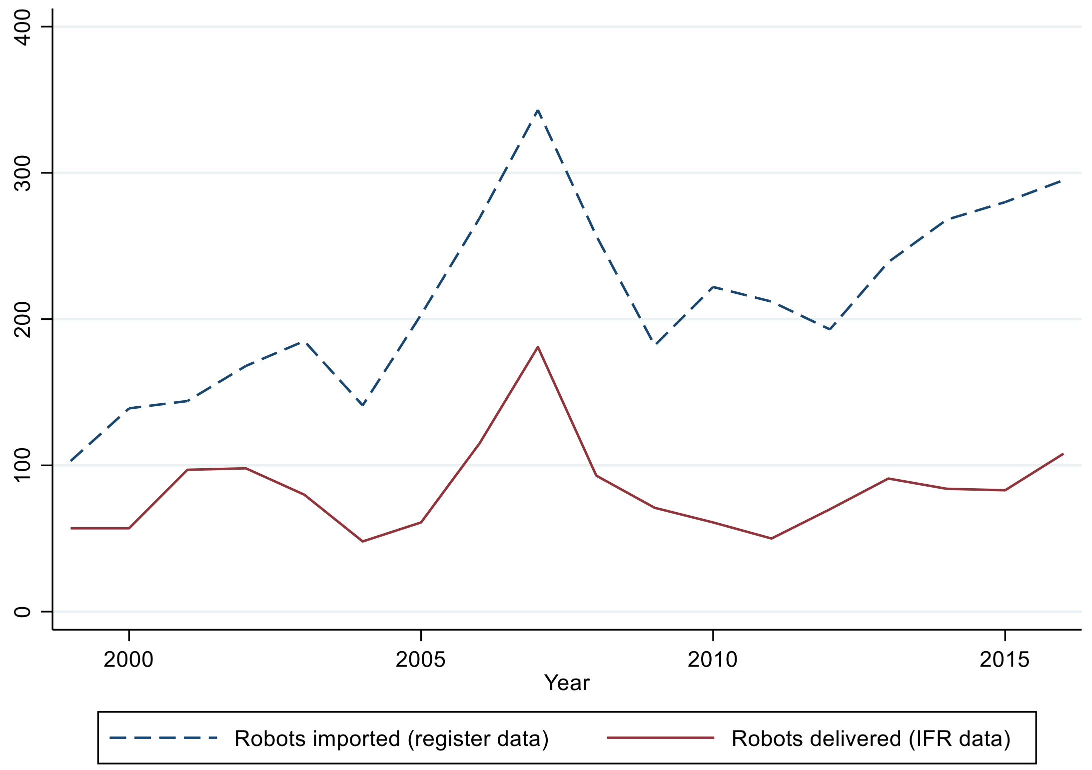
Figure 1.Value of robots imported in Norwegian kroner



Note: The figure shows the yearly total value of industrial robots imported in Norway for all sectors.

As described above, we identify robots based on the import of robots at the firm level. In order to gauge if our approach is captures the number of robots in Norway well we compare our yearly data on robot imports with data from the International Federation of Robotics (IFR) data. The IFR data provides information on the number of newly installed industrial robots per country. IFR compile this data based on a combination of survey information from industrial robot manufacturers and estimations from nation robotic associations. The solid red line in Figure 2 gives IFR's estimates for the number of newly installed robots in Norway. While the number of robots imported yearly is higher using import data than IFR data, the fact that the trends in the number of new industrial robots are similar, is reassuring.

Figure 2: Number of robots in Norway, Import register and IFR data



Note: The figure shows the total number of industrial robots imported in Norway for all sectors using register import data (blue dotted line) and IFR data (solid red line).

The data from the IFR on newly installed robots are potentially lower as the robotics federation obtains most of its information from a survey of industry experts. The survey data is likely to include a less than 100% response rate and therefore underestimate the number of yearly new robots installed in Norway.

6. Results

We first show results from estimating individual wage regressions, using equation (2). Table 1 presents results from four models; Model 1 includes industry fixed effects, Model 2 includes firm fixed effects, Model 3 includes job (match between individual and firm) fixed effects, and Model 4 includes job and time varying firm effects.

Table 1. Log wage regressions with robots. By education. Dependent variable: Log hourly wage Reference group: Upper Secondary

Model	1	2	3	4
Fixed effects specifications:	Industry FE	Firm FE	Job FE	Job FE FirmxYear
Robot	0.0409***	-0.0209*	0.0015	
	(0.0066)	(0.0087)	(0.0094)	
Higher education X Robot	0.0136	0.0372***	0.0840***	0.0455***
	(0.0071)	(0.0068)	(0.0099)	(0.0061)
Below Upper Sec. X Robot	-0.0039	-0.0086*	-0.0587***	-0.0307***
	(0.0047)	(0.0038)	(0.0077)	(0.0047)
Empl. share own education	-0.0837***	-0.0269***	0.0652***	0.1591***
	(0.0054)	(0.0050)	(0.0067)	(0.0061)
R^2	0.259	0.332	0.698	0.715
N	2.84e+06	2.84e+06	2.84e+06	2.69e+06

Note: Models 1 and 2 include gender, age, age square, dummies for higher education, below upper secondary, and unknown education interacted with robot, (reference group: upper secondary), and year dummies. A job-spell fixed effect is the unique combination of the match between an individual and a firm (employment spell), In models 3 and 4 gender and education levels are absorbed in the job dummies, and the linear term for age in the year dummies. In model, 4 the robot dummy is absorbed in the time varying firm effects. See method section for details. Robots is an indicator variable taking the value of 1 from the first year a firm is observed as importing robots and onwards.

Table 1 shows the coefficient of the log wage regression related to the use of robots. Using interaction terms, robots are allowed to have differential impact by education. Upper secondary education is the reference group, and the association between robots and wages for workers with upper secondary education is reported in the first line (Robot). The subsequent interaction terms should be interpreted as the difference between the impacts for the different education groups from the impact for workers with upper secondary education.

In Model 1 we compare firms within the same industry. For workers with upper secondary schooling, firms using robots pay 4 percent more than firms not using robots, and the interaction terms with education are not significant.

Adding firm fixed effects, in Modell 2, has two important consequences. First, the coefficients for workers with upper secondary education drops to a small, but significantly negative effect of about 2 percent. The positive coefficient shown in Model 1 is thus mainly due to a positive correlation between the use of robot technology and a permanent fixed effect of the firm: High wage firms are more likely to use robots. Secondly, the difference between higher and lower education widens, while workers with lower education lose almost 3 percent (-0.02-0.009) by the introduction of robots, workers with higher education gain almost 2 percent higher wages when robots are introduced: Within firms, higher educated workers gain while lower educated lose.

These results may be contaminated by the selection of workers into firms that are more likely to use robots, and by the selection of workers into firms in periods when they use robots relative to periods when they do not use robots. The next column (Model 3) thus shows results for models including job (individual x firm) match effects. Analysing within-job spell wage variation changes the robot coefficient for the reference group (upper secondary school) to about zero. Within job, there appears to be no effect on robots on wages for workers with upper secondary schooling. The results for those with higher education are still positive and much stronger compared to the firm-fixed effect results. The negative result among those with below upper secondary school in Model 3 is also strengthened when job-spell fixed effects are added.

Last, in Model 4, we estimate the model including fixed job-spell and time varying firm effects. This means that we compare wage developments within-job-spell between different groups, taking out a common firm effect each year. The main results are sustained; we still find a positive wage effect for the high skilled workers and a negative wage effect for those with below upper secondary school.

Next, we look at the importance of occupation. Based on occupational ISCO codes, we define five groups of workers: Managers, STEM-workers, Other Professionals, Blue-Collar workers and Other Non-professionals (see data section for details). Table 2 shows the distribution between these groups in total and by education.

Table 2. Occupations and education. Percent

	Percent of all	Percent of occupation by education	
		Less than college	Higher education
Manager	10	53	47
STEM	14	41	59
Professionals	10	54	46
Blue-collar	49	95	5
Other non-professionals	17	89	11
All	100	79	21

Note: Managers is defined as ISCO-08 code=1 (first digit), STEM as ISCO-08 code=21 or 31 (first two digits), Professionals as the remaining in ISCO-08 code 2 and 3, Blue-collar workers as ISCO-08 code 7 and 8 (<83), and Other non-professionals as the remaining ISCO-08 code > 3. Higher education is defined as university or college degree or higher.

10 per cent of the workers in our manufacturing sample are Mangers or professionals, while 14 per cent are in STEM occupations. STEM workers is the only group with a majority of workers with higher education.

Table 3 shows the coefficients of the log wage regression related to the introduction of industrial robots. Now, robots are allowed to have differential impacts on wages by occupation, and education. The presentation of results follow the same procedure, from Model 1 to Model

4, as in Table 1. In this case, upper secondary educated workers in blue collar jobs constitute the reference category.

The within-industry estimates show that managers and professionals have positive wage effects from robots, STEM-workers on the other hand do not. In the three other models, we find positive interactions between all three types of occupations and robots. The size of the coefficients are largest among managers. For the reference occupational group, we find negative effects of robots, in both the firm-fixed and in the job-spell fixed effect model.

Table 3. Log hourly wage regression with robots. By education and occupation

Reference group: Upper Secondary; Blue Collar Workers

Model	1	2	3	4
FE-specifications:	Industry FE	Firm FE	Job FE	Job FE FirmxYear
Robot	0.0479***	-0.0031	-0.0163	
	(0.0070)	(0.0086)	(0.0092)	
Manager x Robot	0.0556***	0.0652***	0.0981***	0.0738***
	(0.0094)	(0.0082)	(0.0120)	(0.0061)
STEM x Robot	-0.0106	0.0379***	0.0688***	0.0453***
	(0.0115)	(0.0093)	(0.0114)	(0.0046)
Professional x Robot	0.0179*	0.0479***	0.0497***	0.0310***
	(0.0083)	(0.0079)	(0.0085)	(0.0049)
Other x Robot	-0.0014	-0.0005	0.0141*	0.0090
	(0.0064)	(0.0062)	(0.0064)	(0.0053)
Higher Education x Robot	-0.0009	0.0050	0.0404***	0.0224***
	(0.0070)	(0.0068)	(0.0084)	(0.0062)
Below Upper Sec.x Robot	0.0067	0.0015	-0.0488***	-0.0260***
	(0.0039)	(0.0031)	(0.0069)	(0.0047)
Manager	0.4479***	0.4537***		
	(0.0025)	(0.0024)		
STEM	0.2424***	0.1961***		
	(0.0043)	(0.0036)		
Professional	0.1748***	0.1515***		
	(0.0033)	(0.0032)		
Other	0.0148***	0.0073***		
	(0.0022)	(0.0021)		
Empl. share own education	-0.0511***	0.0194***	0.0665***	0.1599***
	(0.0049)	(0.0041)	(0.0067)	(0.0061)
R^2	0.310	0.379	0.698	0.715
N	2.84e+06	2.84e+06	2.84e+06	2.69e+06

Note: Models 1 and 2 include gender, age, age square, dummies for higher education, below upper secondary, and unknown education interacted with robot, (reference: upper secondary and blue collar workers), and year dummies. A job-spell fixed effect is the unique combination of the match between an individual and a firm (employment spell), In models 3 and 4 gender and education levels are absorbed in the job dummies, and the linear term for age in the year dummies. In model 4 the robot dummy is absorbed in the time varying firm effects. See method section for details. Robots is an indicator variable taking the value of 1 from the first year a firm is observed as importing robots and onwards.

Table 4 presents results from the step 2 regressions. These are firm-level regressions with the year-specific firm effect, from the "job-spell and time varying firm effects" specification in

Table 3, as dependent variable. Since workers with upper secondary education in blue-collar jobs constitute the reference group in Table 3, the coefficients in Table 4 should be interpreted as the effect of the various covariates on workers with upper secondary education in blue-collar jobs. The models include firm and year fixed effects.

Table 4. Firm level regressions. Dependent variable: year specific firm effect (log hourly wage)

Model	1	2	3	4	5	6
Robot	0.0408*	0.0363*	0.0399*	0.0377*	0.0333*	0.0385*
	(0.0160)	(0.0160)	(0.0156)	(0.0166)	(0.0166)	(0.0163)
Ln Firm employment		0.0455***	0.0378***		0.0348***	0.0257***
		(0.0038)	(0.0038)		(0.0041)	(0.0040)
Ln Sales/Worker			0.1047***			0.0945***
			(0.0024)			(0.0025)
Lag Firm-yr-fe				0.1963***	0.1942***	0.1831***
				(0.0041)	(0.0041)	(0.0040)
R^2	0.732	0.733	0.744	0.760	0.760	0.769
N	50189	50189	50189	44398	44398	44398

Note: Dependent variable is the year specific firm effect calculated from the firmxyear and job-spell fixed effects in Table 3. Since workers with upper secondary education in blue-collar jobs constitute the reference group in Table 3, the coefficients here should be interpreted as the effect of the various covariates on workers with upper secondary education in blue-collar jobs. See text and method section for details. Unit of observation: Firm by year. The models include year and firm specific effects.

We find a coefficient for robot of about 4 percent (Model 3), as the effect of robots on blue-collar workers with upper secondary schooling. The total effect of robots on the earnings of the other groups can be calculated as the sum of 0.04 and the estimated coefficient for the other groups in Table 3. For instance, we find a total effect for managers with higher education of 0.040+0.074+0.022=0.136, which would imply that managers with higher education earn around 14 log points more after the introduction of robots than before. The models in Table 4 may, however, suffer from potential endogeneity problems at the firm level, and, thus, these results should be interpreted with caution.

The last three models adds a dynamic dimension to the model by including the lagged value of the year specific firm effect (lagged dependent variable). In the dynamic specification, we may interpret the coefficient for robots as a short-term effect, while the long-term effect may be calculated by multiplying the short-term effect by $1/(1-\lambda)$ where λ is the coefficient on the lagged dependent variable. Ignoring possible bias in the estimation of the dynamic model (see Nickell 1986), we find a slightly smaller short-term effect, and a long run multiplier of $1/(1-.18) = 1.22$, implying that the long run effect of robots is about 22 percent larger than the immediate effect. Again, these results should be interpreted with caution.

Note, however, that unless the endogeneity problem at the firm level affects different groups differently, or that different groups within the same firm display different dynamics over time, none of the above cautions apply to the results of the previous section, regarding the effects on the within firm wage distributions.

7. Conclusions

Using information on the imports of industrial robots, we analyse the effects of robotisation on wages at the individual and group levels for the manufacturing industry in Norway. We utilise matched employer-employee data with detailed information on the import of robots for all firms in the manufacturing industry in Norway. We contribute to the existing literature by looking directly at firm and individual level impacts of robots, whereas the existing literature has predominantly relied on industry and/or region level data.

Our estimation approach controls for individual fixed effects, match specific effects, and yearly firm effects, in addition to the other time varying covariates. This approach allows us to accurately measure the relative impact of the introduction of industrial robots at the firm level for a given group of employees, relative to the reference group. We investigate relative group effects along two dimensions: education and type of occupation. Firstly, we estimate the relative wage effects of robotisation on employees whose 1) highest achieved education is tertiary education and 2) highest achieved education is below secondary. The reference group is workers with an upper secondary education. Secondly, we look at the relative effects of robotisation on different occupation categories. We classify all workers into occupational groups: managers, STEM workers, professionals, blue-collar workers and other non-professionals. The reference category is blue-collar workers. In a second stage of our estimation, we estimate the effect of robotisation for the reference group.

Our results show a positive association between the use of robots and wages for the average employee in the manufacturing sector in Norway. Adding controls for firm employment, capital per worker and value added per worker does not change the general finding of a positive wage effect, on average. Looking at relative group effects, our findings show that workers with a higher education gain more from the introduction of industrial robots than those with a secondary or below secondary education. Employees in managerial positions benefit more from robotisation than those in STEM or professional occupations, while blue-collar workers and other non-professionals benefit the least.

Given that we control for individual fixed effects, match specific effects, and yearly firm effects, we are most confident about the interpretation of the relative wage effects within firms. Given the scant individual and firm level evidence on the impact of robots, our findings provide new evidence for the existence of uneven effects of robotisation across different groups of workers. Overall, our results are supportive of robots contributing to skilled biased technical change within firms, rather than to polarization. As expected, our results suggest that those with more education have a relatively higher wage gain from robotisation. Low skilled workers gain the least. What perhaps is more unexpected is the finding that the wages of managers increase more after the introduction of industrial robots relative to those in STEM occupations. One might expect that occupations that are directly involved in the programming, implementation and running of industrial robots would gain the most from their introduction.

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