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Trade Unions and the Process of Technological Change

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ABSTRACT

We investigate how trade unions influence the process of technological change at the workplace level. Using matched employer-employee data, comprising all Norwegian workplaces and working individuals in the period 2000-2014, we exploit exogeneous changes in the tax rules for union members to identify how changes in unionization rates affect the structural composition of occupations within workplaces. Making a distinction between routine and non-routine workers, based on their estimated probabilities of being replaced by automation technologies, we show how labor unions contribute to raising the relative wage of routine workers over non-routine workers. As routine workers on average have lower earnings than non-routine workers, unions thereby contribute to compress wages at the workplace level. The direct implication of this policy is shown to reduce the relative demand for routine workers over non-routine workers in unionized establishments. However, our results also suggest that unions influence the relative demand for routine workers, conditional on relative wages. Our findings thus give some support to bargaining theories where unions force firms off their demand curves.

1. Introduction

Ever since Keynes' famously predicted that new technologies would bring the disease of '*technological unemployment*' (Keynes, 1931), the process of technological change and its implications for the labor market has been a source of extensive economic research. In the last decades, the concern of labor-replacing technologies has been fueled by the progress in the use of computers (Autor et al., 2003), industrial robots (Acemoglu & Restrepo, 2020; De Vries et al., 2020), and artificial intelligence and mobile robotics (Brynjolfsson & McAfee, 2012; Frey & Osborne, 2017). Recent studies document evidence of rising inequality following serious structural change in the composition of skills (Acemoglu, 2002; Autor & Dorn, 2013), as well as a decrease in the labor share of income as a result of a slowdown in the creation of new tasks and in the reinstatement of displaced labor (Acemoglu & Restrepo, 2019).

During the same period, most countries have also experienced a decline in unionization rates. While several authors have studied the erosion of unions in conjuncture with technological change, this work has mostly been concerned with answering how the two trends compete in explaining the surge in inequality and the fall of the labor share (Freeman, 1991; Card & DiNardo, 2002; Acemoglu et al., 2001; Piketty, 2014; Krueger, 2018; Guimarães & Gil, 2022). A few studies, however, investigate how technological change may explain variation in union density. Acemoglu et al. (2001) argue how skill-biased technological change (SBTC) could explain declining unionization rates, as larger wage gaps due to productivity differences undermine the coalition among skilled and unskilled workers in support of unions. Acikgoz & Kaymak (2014) demonstrate how SBTC may explain about 40 percent of the decline of unions in the US, both by reducing the incentives of skilled workers to unionize but also by weakening the firms' incentives to hire low-skilled union workers. Dinlersoz & Greenwood (2016) also show how the patterns of unionization in the US during the 20th century may be explained by SBTC. While the surge in unionization rates during the first half of the century is shown to coincide with the diffusion of mass production during the Second Industrial Revolution, the rise of automation and computerization may explain the fall of unions during the second half of the century.

Surprisingly, little effort has been put into understanding the reverse causation, that is how unions may influence the process of technological change. This is what we investigate in the current study. How are firms' incentives to invest in automation altered by the presence of a union and how are unions to respond to this threat of replacing technology?

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Assuming unions lower profitability,[1] the gains in profits from investing in replacing technology in unionized firms should be higher than in non-unionized firms, all else equal. However, if the firm remains unionized, the classical holdup problem (Baldwin, 1983; Grout, 1984), where union rent seeking lowers the return on investments in the absence of binding contracts, still applies. Moreover, by exploiting its bargaining power and by influencing internal relations, unions may have a direct impact on the decision on whether or not to automate tasks previously conducted by labor. It is therefore not obvious whether unionized firms will be more or less eager to invest in replacing technology than non-unionized firms. This is, to a large degree, an empirical question.

Using matched employer-employee panel data, comprising all Norwegian establishments and employees in the period 2000-2014, we exploit exogeneous changes in the tax rules for union members to identify how structural changes in the occupational composition within workplaces are affected by variation in union density. In order to evaluate the technological direction of structural changes, occupations are measured by their estimated risk of automation according to Frey and Osborne (2017). As a test of robustness, we also apply the more widely acknowledged measure of routine-task intensity (Autor et al., 2003). The share of workers in routine occupations is used as a proxy for the technological maturity of workplaces, where a reduction in the share is interpreted as a technological advance. Our approach is therefore to estimate how the presence of a union influences changes in the share of workers in routine occupations.

Our results suggest that unions contribute to raising the relative wage of routine workers over non-routine workers. As routine workers on average have lower earnings than non-routine workers, unions thereby contribute to compress wages at the workplace level. The direct implication of this policy is shown to reduce the relative demand for routine workers over non-routine workers. However, our results also suggest that unions influence the relative demand for routine workers, *conditional* on relative wages. In other words, our study identifies two potentially opposing channels through which unions influence the process of technological change.

While more empirical evidence on how unions alter technological change has been called for (Acemoglu & Autor, 2011, p. 1160), both of the two channels identified above are previously explored in the literature. On the one hand, there is a rich literature on how unions affect both the levels and distribution of wages. The monopoly bargaining power of unionized workers is widely recognized to add a union-premium on wages (Doucouliagos et al., 2017, p. 149). In isolation, a positive union wage premium implies stronger incentives to replace labor with new technology. Furthermore, unions are often believed to compress the distribution of wages, both within firms (Svarstad & Nymoen, 2022) and at the macro level in countries with a centralized or coordinated bargaining structure (Moene & Wallerstein, 1997; Haucap & Wey, 2004; Braun, 2011; Dale-Olsen, 2021). Wage compression contributes to making low-skilled labor relatively expensive and highly skilled labor relatively cheap. In line with theories of skilled-biased technological change, low-skilled labor is also more replaceable by automation technology, while high-skilled labor is more likely to complement this technology (Acemoglu, 2002).

However, if unions are able to capture a share of the quasi-rents of investments in new technology, this can be shown to reduce firms' optimal investments in absence of binding wage contracts (Baldwin, 1983; Grout, 1984). The risk of rent-seeking lowers the expected return and thus the level of investments.[2] This finding led Freeman and Medoff (1984, p. 170) to conclude that the effect of unionization on technological advance is theoretically ambiguous. In a recent study of the Norwegian manufacturing sector by Barth et al. (2020), higher union density is found to increase firm-level productivity, as measured by value added per worker. However, the authors also find that the union wage premium is increasing in value added per worker, which indicates rent-seeking behavior. In other words, while unionized firms may face stronger incentives to substitute labor for capital due to union wage premiums, union rent seeking may lower the returns on investments.

On the other hand, unions may also alter a firm's investment decision directly through their presence in the organization. Indeed, local union representatives often work in close relationship with the management.[3] By exploiting its bargaining power and by influencing internal relations, unions may acquire *de facto* influence in the managerial strategic operations. This mechanism is part of what Freeman and Medoff (1982) called the '*relative inelasticity hypothesis*', which states that labor demand is less elastic in unionized firms.[4] In effect, unions '*force employers off their demand curves*' (Maki & Meredith, 1987). That is, not only may unions affect investments indirectly through their impact on labor costs. They may also have a direct impact on the investment decisions.

If unions influence firms' investment decisions, the effect of unions on technological change will depend on the local union's attitudes to technology. Carmichael & MacLeod (1993) develop a simple model that illustrates how multiskilled workers may benefit from the productivity gains of new technology, while specialized workers lose as they are more difficult to relocate within the organization. In a related paper, Dowrick & Spencer (1994) examine the conditions under which unions will embrace or oppose technological change within a framework of oligopolistic competition in the product market. In their model, unions may rationally take the role as 'Luddites' if labor demand is sufficiently inelastic and if union preferences are weighted in favor of jobs. Building on a similar framework, Lommerud et al. (2006) show how globalization tends to make technology opposition from unions more likely, and that technology opposition is stronger in more technologically advanced countries.

Based on a meta-regression of 20 different empirical studies, Doucouliagos et al. (2017, pp. 86-109) conclude that unionization seems to have a modest negative effect on physical capital formation. However, the survey documents a stronger negative association between unions and intangible capital investments,[5] which may be a better indicator of union resistance to technology investments. Cross-country differences are found to be largely driven by labor market regulations, where union resistance to technology seems to be lower in more regulated labor markets. This finding is important in the Norwegian context, where the Working Environment Act together with centralized collective bargaining and firm level agreements form an important regulatory framework for industrial relations (Svarstad & Kostøl, 2022).

Our study adds an important contribution to the literature on the interactions between trade unions and technological change. While most previous studies have been concerned with how unions are affected by technology, we identify two mechanisms through which unions may influence the process of technological change within a simple efficient bargaining model. Moreover, we provide causal evidence of these mechanisms using rich panel data covering all Norwegian workplaces and working individuals in the private sector.

The remainder of the paper is organized as follows. Section 2 develops a theoretical framework for analyzing how unions alter the occu-

[1] While unions may succeed in raising productivity through voice-effects and organizational change (Freeman & Medoff, 1984), this effect is assumed to be more than canceled by union wage premia. Indeed, this is also the finding in the comprehensive meta study of Doucouliagos et al. (2017).

[2] If the union can credibly commit its wage for a sufficiently long time, however, Tauman & Weiss (1987) illustrate how unionization, under certain conditions, may encourage the adoption of labor-saving technology.

[3] See e.g., Huzzard et al. (2004) for a discussion of strategic unionism and partnership.

[4] Note, however, that this finding could also reflect a higher probability of unionization and survival of unions in firms or sectors where labor demand is more inelastic.

[5] Intangibles include R&D, patents, goodwill etc. The negative correlation between unionism and R&D is found to be larger than with innovations and patents.

pational composition within workplaces. In Section 3, we present our empirical strategy and discuss issues of identification. We describe our data and present descriptive statistics in Section 4, while Section 5 documents our results. Section 6 concludes.

2. Theoretical framework

The purpose of this study is to investigate how unions influence the process of technological change at the workplace level, by altering the adoption of new technology. In this section, we outline a simple conceptual model to highlight two such mechanisms. While we will not attempt to estimate the structural parameters of the conceptual model, the model motivates our empirical specifications later in the paper. The model takes as a starting point the theory of routine-biased technological change (Autor et al., 2003; Autor et al., 2006; Goos & Manning, 2007; Autor & Dorn, 2013), and then extends this approach to include labor unions.

2.1. Technology

Let the output of an establishment be determined by the following generalized CES production function, where L_R and L_N denote the use of routine and non-routine labor input, respectively:

$$Y = \left[\alpha\left(A_R L_R\right)^{\eta} + (1-\alpha)\left(A_N L_N\right)^{\eta}\right]^{\frac{\upsilon}{\eta}}, \quad (1)$$

where η denotes the substitution parameter, with the elasticity of substitution between routine and non-routine labor defined by $\sigma = \frac{1}{1-\eta}$, α denotes the distribution parameter, while A_R and A_N represent factor-augmenting technology terms. υ measures the degree of homogeneity of the production function, where $\upsilon = 1$ corresponds to the standard CES production function with constant returns to scale.

In the case of competitive labor markets, the wage paid to each type of worker is given by the value of their marginal product. That is, the wage paid to routine workers is given by:

$$w_R = \frac{\partial Y}{\partial L_R} = \upsilon\alpha A_R^{\eta} L_R^{\eta-1} Y^{\frac{\upsilon-\eta}{\upsilon}}, \quad (2)$$

whereas the wage paid to non-routine workers is:

$$w_N = \frac{\partial Y}{\partial L_N} = \upsilon(1-\alpha) A_N^{\eta} L_N^{\eta-1} Y^{\frac{\upsilon-\eta}{\upsilon}} \quad (3)$$

It then follows that the relative wage paid to routine workers over non-routine workers is:

$$\omega \equiv \frac{w_R}{w_N} = \frac{\alpha}{1-\alpha}\left(\frac{A_R}{A_N}\right)^{\eta}\left(\frac{L_N}{L_R}\right)^{1-\eta} \quad (4)$$

If we keep the relative supply of routine and non-routine workers fixed, routine-biased technological change will affect the relative pay. We define technological change to be biased towards non-routine labor if it contributes to lowering the relative pay of routine workers. This amounts to an increase (decrease) in $\frac{A_R}{A_N}$ if the elasticity of substitution is smaller (larger) than unity.[6]

Under perfect competition, workplaces take wages as given and minimize costs conditional on some level of output. The workplace's relative conditional demand function is then given by the optimality condition in (4), which rearranged and in natural logarithms yields:

$$\log\left(\frac{L_R}{L_N}\right) = -\sigma\log\left(\frac{1-\alpha}{\alpha}\right) + (\sigma-1)\log\left(\frac{A_R}{A_N}\right) - \sigma\log\left(\frac{w_R}{w_N}\right) \quad (5)$$

That is, the optimal demand for routine workers over non-routine workers is determined by relative wages, relative productivity, the elasticity of substitution, and the distribution parameter α. The optimal demand will change in response to changes in relative wages and routine-biased technological change.

2.2. Workers

Workers supply one unit of labor each and receive no disutility from work. They are randomly equipped with skills qualifying for a job as either routine or non-routine worker. Workers choose to organize in labor unions if the utility from doing so exceeds the utility from not being organized. We will denote the wage paid to worker of type i by w_i^u if unionized and w_i if not, where the non-union wage of each group equals its marginal product of labor. The price on union membership is equal to $c(1-\lambda)$, where λ denotes a government subsidy of union membership. Moreover, as in Barth et al. (2020), we allow heterogeneous political preferences regarding union membership, by discounting the cost of union membership with $1+\varepsilon$, where $E(\varepsilon) = 0$. The participation constraint for joining a union is then given by:

$$w_i^u - \frac{c(1-\lambda)}{1+\varepsilon} \geq w_i, \; i = R, N \quad (6)$$

From (6) it is clear that union participation depends positively on the union wage premium, the government subsidy rate and union-friendly preferences, and negatively on the union membership fee.

2.3. Unions

Labor unions organize both routine and non-routine workers in the same local union at the workplace level. They face a constant unit cost per organized member equal to $\tilde{c}$, which is financed exclusively by the membership fee c per member. As a simplification, we impose a restriction that $c = \tilde{c}$, which implies that unions are not allowed to save or lend money. The local union is assumed to maximize an objective function equal to the expected utility of a representative union member. We use $\Omega = \Omega_R + \Omega_N$ to denote the pool of routine and non-routine union members available to the firm, while w_i^u and b_i denote the union wage rate and the reservation wage paid to workers of type $i = R, N$. With state-independent utility, the union's objective function is then given by:[7]

$$V = \frac{L_R}{\Omega}\left(u\left(w_R^u\right) - u(b_R)\right) + \frac{L_N}{\Omega}\left(u\left(w_N^u\right) - u(b_N)\right) + \bar{V}, \quad (7)$$

where $\bar{V} \equiv \frac{\Omega_R}{\Omega}u(b_R) + \frac{\Omega_N}{\Omega}u(b_N)$ represents the disagreement outcome, defined by the reservation wages of the two groups of workers multiplied by their respective shares in the available workforce. The reservation wage reflects the workers' outside option, which may differ between routine workers and non-routine workers. As we will see shortly, the possibility of different reservation wages has important implications for the predictions of the model.

The local union and the firm are assumed to simultaneously determine wages and employment of routine and non-routine workers in a bargaining process. The bargaining is efficient, in the sense that the outcome Pareto dominates the outcome of a bargaining over wages only (McDonald & Solow, 1981). If we let $\pi = Y - w_R^u L_R - w_N^u L_N$ denote the profit of the firm, where the product price is set equal to unity, the outcome of the efficient bargaining is given by the solution of the following Nash problem:

$$\max_{\{w_i, L_i\}} \left(V - \overline{V}\right)^{\mu}\left(\pi - \overline{\pi}\right)^{1-\mu}, \quad i = R, L, \quad (8)$$

where $\bar{\pi}$ denotes the minimum profit requirement of the firm, and μ denotes the bargaining strength of the union.[8] The four first-order con-

[6] This is found by differentiating (4) with respect to A_R/A_N.

[7] To see this, note that the expected utility of a representative union member is given by the expected utility of a unionized routine worker times the fraction of routine workers, plus the expected utility of a unionized non-routine worker times the fraction of non-routine workers. The local union treats the pool of workers available to the firm as given and does not consider how the bargaining outcome may affect aggregate union memberships in the economy.

[8] The bargaining strength of unions could, in principle, reflect multiple factors like e.g., the size of strike funds, the business cycle or the legal position of unions

ditions from the maximization problem are given by:

$$\frac{\mu}{V-\bar{V}}\frac{L_R}{\Omega}u'\left(w_R^u\right)+\frac{1-\mu}{\pi-\bar{\pi}}\left(-L_R\right)=0 \tag{9}$$

$$\frac{\mu}{V-\bar{V}}\frac{L_N}{\Omega}u'\left(w_N^u\right)+\frac{1-\mu}{\pi-\bar{\pi}}\left(-L_N\right)=0 \tag{10}$$

$$\frac{\mu}{V-\bar{V}}\frac{u\left(w_R^u\right)-u\left(b_R\right)}{\Omega}+\frac{1-\mu}{\pi-\bar{\pi}}\left(\frac{\partial Y}{\partial L_R}-w_R^u\right)=0 \tag{11}$$

$$\frac{\mu}{V-\bar{V}}\frac{u\left(w_N^u\right)-u\left(b_N\right)}{\Omega}+\frac{1-\mu}{\pi-\bar{\pi}}\left(\frac{\partial Y}{\partial L_N}-w_N^u\right)=0 \tag{12}$$

If we combine (9) and (10), we immediately arrive at the result that the marginal utility of earning the routine wage should equal the marginal utility of the non-routine wage. As long as we assume smooth utility functions, this implies equal wage rates for the two types of workers, irrespective of their marginal products. This is due to the properties of the utilitarian objective function of the union, see e.g., Cahuc et al. (2014, pp. 441-443). In other words, the model predicts full wage compression.

By combining (9) with (11) and (10) with (12), we can derive the pairs of *contract curves:*

$$\frac{\partial Y}{\partial L_i}-w_i^u=-\frac{u\left(w_i^u\right)-u\left(b_i\right)}{u'\left(w_i^u\right)},\ i=R,L \tag{13}$$

The contract curves trace out all pairs of (w_i, L_i) where the union's indifference curves are tangent to the firm's isoprofit curves. Using the above result of full wage compression, $w_R^u = w_N^u = w^u$, the contract curves reduce to the following result:

$$\frac{\partial Y}{\partial L_R}-\frac{\partial Y}{\partial L_N}=\frac{u\left(b_N\right)-u\left(b_R\right)}{u'(w^u)} \tag{14}$$

That is, the contract curves implicitly define the firm's relative employment of routine and non-routine workers. Consider first the case where the reservation wages of the two groups of workers are equal, in which case (14) reduces to $\frac{\partial Y}{\partial L_R}=\frac{\partial Y}{\partial L_N}$. This is equivalent to the condition for optimal relative input demand in the case of equal wage rates. In other words, in this case *relative* employment will be consistent with the firm's optimal relative demand. However, if the reservation wage is higher for non-routine workers than for routine workers, relative demand for routine workers will be lower than in the competitive case. In the opposite case when the reservation wage for non-routine workers is lower than for routine workers, relative demand for routine workers will be higher. In other words, the contract curves illustrate how the union influence the relative employment of routine workers and non-routine workers, conditional on the relative wage, as a function of the relative reservation wages of the two types of workers.

We have now shown how unions are predicted to influence both the relative wage, *and* the relative employment conditional on the relative wage, using a simple model of efficient bargaining. To see the impact on the wage levels, which are equal, we may derive the pairs of *rent division curves* by combining the contract curves in (13) with (9) and letting $w_R = w_N = w^u$:[9]

$$w^u=\mu\frac{(Y-\bar{\pi})}{L_R+L_N}+(1-\mu)\frac{L_R\frac{\partial Y}{\partial L_R}+L_N\frac{\partial Y}{\partial L_N}}{L_R+L_N}, \tag{15}$$

The rent division curves show how wages are determined as weighted averages of marginal and average productivity, where the weights are given by relative bargaining strength. As long as the production technology exhibits decreasing returns to scale, corresponding to $\upsilon < 1$ in the production function in (1), average productivity will be greater than marginal productivity, and the union wage level will be higher than in the competitive case.[10]

While the conceptual model outlined in this section is highly stylized, it illustrates how unions may influence technological change through two key mechanisms. On the one hand, unions compress wages between routine and non-routine workers. If routine workers on average have lower earnings than non-routine workers, which we will indeed demonstrate in the following sections, this effect will contribute to increase the relative wage of routine workers over non-routine workers. In isolation, this "wage channel"-effect will accelerate the process of routine-biased technological change if relative employment is determined by the firm's relative demand curve. On the other hand, however, as unions and firms bargain over both wages and employment, unions may force firms off their relative demand curves. In other words, unions may prevent firms from choosing the optimal combination of routine and non-routine workers conditional on the relative wage. This effect could potentially either dampen or amplify the accelerating effect on technological change through the wage channel, depending on how the reservation wages of the two types of workers compare. This is ultimately an empirical question.

3. Methodology

In this section, we describe our empirical strategy for unveiling how unions influence the process of technological change. The theoretical framework developed in the last section illustrates how unions may influence technological change through two channels. On the one hand, unions are predicted to accelerate technological change by compressing wages between routine and non-routine workers. On the other hand, unions may also influence technological change by altering the firm's relative labor demand conditional on relative wages. While our empirical specifications use these theoretical predictions as guidance, we do not directly estimate the underlying structural parameters of the theoretical model.

The analysis is performed in two steps. In the first step, which is described in Section 3.1, we investigate how unions alter the relative wage paid to routine workers over non-routine workers. Section 3.2 then describes the second step of the analysis, where we investigate how unions alter the pace of technological change in firms *conditional* on relative wages. To account for potentially endogenous selection into unions, we exploit exogeneous changes in the tax rules for union members. This identification strategy is described in Section 3.3.

3.1. How unions alter relative wages

The question of how unions alter the wage paid to routine and non-routine workers may be analyzed at the individual level by estimating a simple Mincer earnings equation (Mincer, 1974), controlling for unionization, whether or not the individual is occupied in a routine or non-routine occupation, as well as the interaction between these two effects. The interaction term will then inform us how the union's impact on wages differs between routine and non-routine workers.

In Norway, union wages are settled in a hierarchy of collective agreements, which are invoked by the labor union if the union density within the establishment reaches certain thresholds. Local agreements automatically extend to all workers in occupations covered by the agree-

in general. However, in the empirical analyses of how unions influence relative wages and relative demand for routine workers over non-routine workers, we will measure the union's bargaining strength by the union density among the workers at the workplace level.

[9] To see this, insert for $V-\bar{V}$ and $\pi-\bar{\pi}$ in (9). Next, insert for $u(w_i^u)-u(b_i)$ using the contract curves in (13), and then use the result that $w_R = w_N = w^u$. See Booth (1995, pp. 128-134) for further details in the case of a single-input production function.

[10] Note that in the case of constant returns to scale ($\upsilon = 1$), in which case average productivity equals marginal productivity, the wage rate becomes independent of the union's bargaining strength under the zero-profit condition, see Agell & Lommerud (1992).

ment, irrespective of individual union membership.[11] While the gains from local bargaining may be higher for union members than for non-members, central provisions in the collective agreement heavily influence the wage paid to both union and non-union members. This implies that the effect of unions on wages is best reflected using workplace union density, instead of individual membership, as our measure of unionization. We therefore estimate the following equation:

$$\log w_{it} = \beta_0 + \beta_1 R_{it} + \beta_2 UD_{it} + \beta_3 R_{it} \times UD_{it} + \boldsymbol{X}_{it}\boldsymbol{\gamma} + u_i + \delta_t + \epsilon_{it}, \quad (16)$$

where w_{it} denotes the nominal wage of individual i in year t, measured as total payments per hour, including bonuses and supplementary pay for uncomfortable working hours. The vector $\boldsymbol{X}_{it}$ comprises individual workers' characteristics,[12] while u_i denotes fixed effects at the individual level, δ_t yearly dummies, and ϵ_{it} random shocks. R_{it} is a dummy variable taking the value 1 if the individual is occupied in a routine occupation and zero otherwise. UD_{it} denotes the union density at the individual's workplace if the individual is employed in a non-routine occupation, while $R_{it} \times UD_{it}$ measures the effect of workplace union density for individuals employed in routine occupations.

The theoretical model in Section 2.3 predicts that unions will compress wage levels. As we will document in the descriptive statistics in Section 4, the average wage paid to routine workers is lower than the wage paid to non-routine workers. Our theory thus predicts a positive interaction effect between workplace union density and having a routine occupation. That is, we expect a positive value of β_3, which is our primary parameter of interest.

3.2. How unions alter technological change

The theory of efficient bargaining presented in Section 2 implies that unions influence employment decisions and potentially force firms off their labor demand curves. This is in contrast to the monopoly theory of unions or the "right to manage" model, where the union dictates or bargain wages, respectively, while employment is determined by the firm's demand curve. A simple test of whether unions alter technological change by influencing the relative demand for routine labor over non-routine labor, is to estimate the relative labor demand function in (5) including a term capturing the presence of unions in the establishment. That is, we estimate

$$\log\left(\frac{L_R}{L_N}\right)_{jt} = \alpha_0 + \alpha_1 \log\left(\frac{w_R}{w_N}\right)_{jt} + \alpha_3 UD_{jt} + \boldsymbol{Z}_{jt}\boldsymbol{\gamma} + \delta_t + u_j + \varepsilon_{jt}, \quad (17)$$

where $(L_R/L_N)_{jt}$ denotes the relative use of routine workers over non-routine workers in establishment j in year t, and $(w_R/w_N)_{jt}$ the corresponding relative wage. α_1 should thus be interpreted as the negative of the elasticity of substitution between routine and non-routine labor. δ_t captures any time-specific shocks common to all companies.[13] The vector $\boldsymbol{Z}_{jt}$ comprises workplace-level shares of individual workers' characteristics, while u_j and ε_{jt} denotes fixed effects at the workplace level and random shocks, respectively. Again, UD denotes workplace union density.

If unions only bargain over wages, we would expect to find $\alpha_3 = 0$ in (17). A rejection of the null hypothesis of $\alpha_3 = 0$ would thus indicate that unions also influence employment decisions, thereby forcing firms off their relative demand curves. Within the efficient bargaining model presented in Section 2, the direction of how unions influence relative employment is determined by which group of workers has the largest reservation wage.[14] Going beyond the theoretical model, however, we may interpret α_3 as an expression of the union's attitude towards new technology. A positive value of α_3 implies that the relative demand for routine workers over non-routine workers increases with union density, conditional on how unions influence the relative wage. This could indicate union resistance towards new technology. On the contrary, a negative value of α_3 could indicate that unions embrace new technology.

One concern with the specification in (17) is the problem of unobserved productivity differences between workers, which are likely to be correlated with both wages and relative labor demand. More precisely, the wage paid to specific routine workers may reflect individual abilities not captured by the broad measure of routine workers, which is likely to comprise a very heterogeneous group of workers. While some of this heterogeneity may be controlled for by including various covariates reflecting individual characteristics, we cannot rule out the possibility that innate productivity differences will bias our estimator. To control for this, we replace firm-level wages with aggregate measures of market wages. Aggregate wages are constructed as average hourly wages within occupation by industry cells at the two-digit level, leaving us with a total of 2,993 market wage cells. As unions are likely to increase wage levels, we calculate separate sets of market wages for workers employed in unionized and non-unionized establishments, respectively.[15]

3.3. Identification

A serious concern relates to the causal interpretation of both equations (16) and (17). While union density may have an impact on relative labor demand, the structural composition of workers in a firm is also likely to have an impact on the union density, as the propensity to join a union may vary systematically across occupations. If routine workers are more likely to join a union than non-routine workers, a change in the relative demand for routine workers over non-routine workers is likely to affect union density. In order to say anything about causal effects, we are therefore dependent on some source of exogenous variation in unionization unrelated to the structural composition of occupations in the firm.

As indicated in Section 2, the propensity to join a union is a function of the union due. In Norway, as in many other countries, union dues are deductible in tax assessments. However, the deductible amount is limited by a cap, and this cap has changed several times during our period of analysis due to changes in political leadership (see Fig. 1). Assuming union membership is an ordinary good, the demand for memberships will adapt when the price changes. It is therefore likely that changes in the rules for tax deduction of union dues will have some effect on the firm-level union density, which is also the finding of Barth et al. (2020), who were the first to exploit this source of exogenous variation. As changes in the government subsidy of union memberships are not correlated with the structural composition of occupations in a given firm, they may act as an instrument for union density.

In constructing our instrument, we utilize data on actual individual payments of union dues. As changes in tax rules for union members affect incentives to unionize also among individuals who are not union members, we follow the strategy of Barth et al. (2020) and construct hypothetical unions based on occupations (at the 3-digit level) within industries (at the 2-digit level). For each existing union member, we calculate the average membership fee within each hypothetical union each

[11] See Appendix A3 for a brief overview of the Norwegian institutional context, and Svarstad & Kostøl (2022) for a more detailed presentation of the Norwegian system of collective agreements.

[12] Individual workers' characteristics include education, age, sex, immigration status, and a distinction between part-time and full-time workers.

[13] Such shocks to relative demand may reflect nonneutral technological changes (Katz & Murhpy, 1992).

[14] If the reservation wage of routine workers is higher (lower) than for non-routine workers, we would expect α_3 to be positive (negative). In the case of equal reservation wages, the bargaining solution for relative employment will coincide with the firm's optimal relative demand conditional on relative wages.

[15] We use information on whether or not firms participate in collective agreements to distinguish unionized from non-unionized firms. To see whether our results are robust to the choice of wage measure, we try different specifications using either actual wages, market wages, or market wages controlling for unionized and non-unionized establishments.

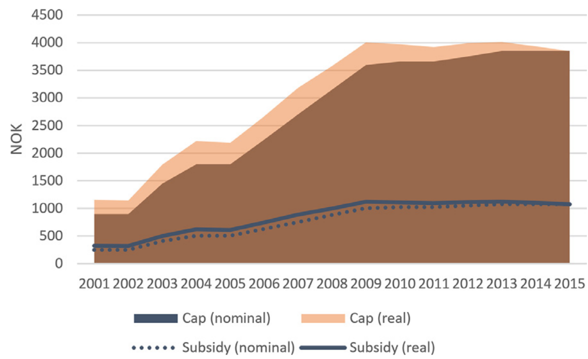

Fig. 1. Changes in the cap on tax deduction of union fees and the realized tax subsidy in NOK. Note: The figure illustrates both nominal and real changes in the cap on union due deductions on the tax schedule, measured in NOK (1000 NOK is approximately equal to €88). The subsidy is defined as the cap multiplied by the marginal income tax (28 percent).

year, excluding the individual's own contribution to the mean. The tax subsidy is then calculated as the product of the income tax (28 percent) and the minimum of the imputed due and the cap on tax deductions. That is, $Subsidy = 0.28 \times \min(\overline{due}, \ cap)$.

One concern with our specification of the tax subsidy is that union dues may be affected by the cap on union due deductions. To control for this, as well as the less likely issue of endogenous occupational composition, we fix the imputed union due within workplaces at the first year of observation in the data. The average workplace due is then determined by the occupational composition the first year, only adjusted for price changes. In addition to the tax subsidy, we also include the workplace average imputed due, fixed at the first year of observation, net of the tax subsidy in our regressions. That is, we include $ND_j \equiv \overline{due}_{j0} - Subsidy_j$, where $\overline{due}_{j0}$ denotes the average imputed union due within workplace j fixed at the first year of observation of the workplace.

4. Data

The data cover the Norwegian private sector in the period 2000-2014 and consist of individual wage data, matched with several other sources of register data related to both firms and employees. The most important data sources are the State Register of Employers and Employees (the '*Aa-register*') matched with the Register of End of the Year Certificate (the '*LTO register*'), as well as Statistics Norway's Wage Statistics. We have information on earnings, hours worked and occupation for each individual. Monthly earnings include agreed monthly earnings, irregular supplements, and bonuses. In order to compare part-time and full-time employees, we calculate hourly wages for each individual every year of observation, based on monthly earnings and reported working hours. Educational statistics are attached, as well as country of origin and other individual characteristics. Variables such as workplace industry and sector are obtained from the Register of Legal Entities and Statistics Norway's Business and Enterprise Register (VoF). Person-related identities are obtained from the Central Population Register (DSF). Individuals, workplaces, and firms have their own unique identifying number, enabling us to track the units across time.

The analysis of how unions alter relative wages relies on observations of individuals covered by the Wage Statistics of Statistics Norway. While the Wage Statistics is based on a sample of establishments – in contrast to the 'Aa-register', which cover all wage earners – the Wage Statistics is known to be a more reliable source of wage data, as it is specifically designed for this purpose.[16] This still leaves us with an individual level dataset containing 2,246,620 unique individuals across 98,263 private sector workplaces, amounting to 11,806,896 individual observations in total for the 15-year period. The analysis of how unions influence relative employment, however, is based on information on all wage earners aggregated to the establishment level, leaving us with 1,685,821 observations of 275,534 workplaces. Because workplaces are established and dissolved throughout the period of analysis, our panel is unbalanced.

Information on individual union membership is derived from data on union dues, which is reported to the tax authorities by the unions. Based on the membership payments, we calculate workplace level union density as the ratio of union members relative to the number of employees in the establishment. Whether a firm participates in a collective agreement or not is derived from membership data from the private sector collectively agreed pension scheme ('*Fellesordningen for AFP*'), in which all firms who are members are also part in a collective agreement.[17]

4.1. Measure of technological change

We rely on changes in the occupational composition within workplaces as our measure of technological change. Our primary measure is based on occupational risk of automation. Each individual in the data set is linked to a four-digit occupational code each year observed. The occupational classification is matched with the estimated risk of automation according to Frey & Osborne (2017). The estimated probabilities rely on a qualitative assessment made in a workshop with an expert team at the Engineering Sciences Department at the Oxford University. The team is asked whether 70 selected occupations in the SOC-classification can be performed by computer technology within 10-20 years. Combining the answers from this workshop with a standardized and measurable set of occupational characteristics from O*NET, the authors estimate automation probabilities for a total of 702 six-digit occupations in the SOC-classification using a logistic regression.[18] When converted to the four-digit ISCO-08 classification standard used in Norway, this leaves us with automation probabilities for 374 occupations. Probabilities for the remaining 23 occupations in the Norwegian classification of occupations are calculated by averaging probabilities for higher level occupations in the nomenclature.

Using the estimated occupational risk of automation, workers are divided into two groups, based on whether their occupation is associated with a high or low risk of being automated within the next 10-20 years. Following the same probability threshold as in Frey & Osborne (2017), occupations with an estimated risk of automation exceeding 0.7 are defined as "high risk" occupations, while occupations with a lower probability of automation are defined as "low risk". With reference to the distinction between routine and non-routine workers in Sections 2 and 3, routine workers are employed in high-risk occupations, while non-

[16] The sampling applied by Statistics Norway is based on stratified random, systematic cluster selection, where the stratification is made by enterprise size (number of employees) in each industry, with complete counting in the largest companies, and cut-off in the smallest. However, all employees in the sampled establishments are included. See https://www.ssb.no/omssb/tjenester-og-verktoy/data-til-forskning/lonn/data_lonn.

[17] Some firms in the sample are covered by collective agreements, without being members in '*Fellesordningen*'. This mainly applies to establishments within shipping, the oil industry and privately run health and social services. The firms in question are manually coded as covered.

[18] For each of the 70 selected occupations in the 'training data', the team determines whether or not the occupations, based on their current composition of tasks, can be performed by automation technology within the next 10-20 years, assigning the occupations 1 if automatable, and 0 if not. The authors then identify nine variables in the O*NET database that describe the level of perception and manipulation, creativity, and social intelligence to perform the tasks of the occupation. They then use a logistic regression to estimate how each of these attributes contribute to the likelihood of automation using the training data. The estimated parameters of each attribute are finally used to predict the likelihood of automation using data on all occupations. Formally, they estimate the automation probability of occupation i as $P_{aut_i} = \frac{1}{1+e^{-\ell_i}}$, where $\ell_i = \boldsymbol{x}^T\boldsymbol{\beta}$ defines the log-likelihood function, $\boldsymbol{x}$ the vector of attributes, and $\boldsymbol{\beta}$ the corresponding parameters to be estimated.

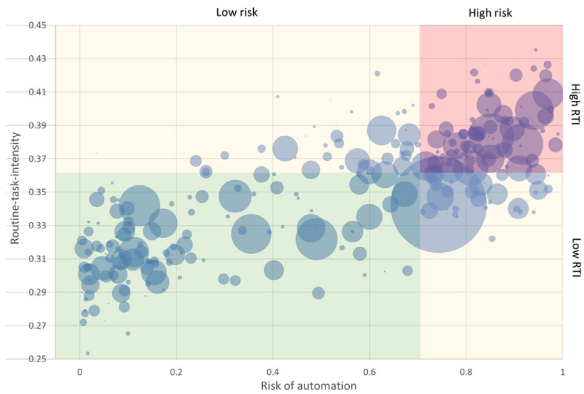

Fig. 2. Correlation between estimated risk of automation and a measure of routine task intensity. Note: The bubbles represent occupations, the size of which determined by their relative frequencies in the data. Risk of automation refers to the estimated risks of computerization in Frey & Osborne (2017), where occupations are classified as 'High risk' if the risk exceeds 0.7. Routine-task-intensity (RTI) is constructed using occupational descriptions from O*NET as in Acemoglu & Autor (2011), where 'High RTI' refers to occupations in the top employment-weighted third of routine task intensity (see Autor & Dorn 2013).

routine workers are employed in low-risk occupations. Finally, technological change is defined as changes in the relative use of routine workers over non-routine workers.

As the probability threshold that defines high-risk occupations in Frey & Osborne (2017) seems somewhat arbitrary, we also test specifications using different thresholds, as well as a continuous measure of automation risk. Moreover, as the approach in their study has been subject to wide criticism (see e.g., Arntz et al. 2016), we also test the more widely applied measure of routine task intensity (RTI) as a robustness check. Exploiting datafiles on occupational abilities, skills, work activities and work content from O*NET, we extract relevant variables and convert occupational codes to the European ISCO classification using the code prepared by Hardy et al. (2018). Following Acemoglu & Autor (2011), we construct five composite task measures which are then used to calculate occupational RTI.[19] As in Autor & Dorn (2013, p. 1571), we then use RTI to identify routine workers as workers employed in occupations that are in the top employment-weighted third of routine task intensity.

The concepts of RTI and risk of automation are closely related, as routine tasks are more easily automated than non-routine tasks. Hence, RTI is often used as a proxy of automation risk (see e.g., Acemoglu & Restrepo, 2022). We have illustrated the correlation between the two measures in the bubble chart in Fig. 2, where the bubbles represent occupations, the size of which determined by their relative frequencies in the data. The plot shows a clear positive correlation between automation risk and RTI, with a correlation coefficient equal to 0.73. Furthermore, the figure illustrates how the binary division of the two measures correspond to each other.[20] The green box in the bottom left corner of the figure contains occupations with both a low risk of automation and a low RTI. The red box in the upper right corner of the figure contains occupations with both a high risk of automation and high RTI. The yellow boxes in the top left and bottom right corner, however, contain occupations with non-corresponding binary measures.

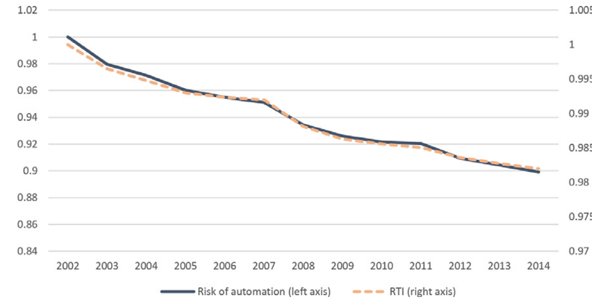

Fig. 3. Average risk of automation and routine task intensity (RTI) among Norwegian full-time employees (2002=1)

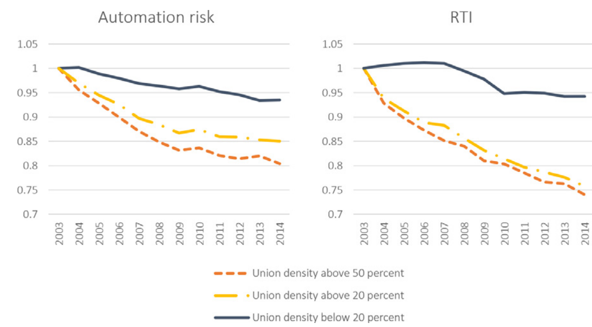

Fig. 4. Mean share of routine workers in establishments with a minimum of 10 employees. Union density below 20 percent,. above 20 percent and above 50 percent. 2003=1. Note: The figures illustrate the evolution of the mean share of routine workers in establishments with a minimum of 10 employees, using occupational risk of automation and RTI, respectively, for different levels of union density. The average measures are set equal to unity in 2003.

4.2. *Descriptive statistics*

We use structural changes in the composition of occupations, as measured by automation risk or routine task intensity (RTI), to proxy technological change. It is thus natural to ask how the measures change over the sample. While the occupational measures are kept constant all years, technological change is reflected by changes in the composition of workers employed in different occupations. In Fig. 3, we illustrate how the average risk of automation (left axis) and the average RTI (right axis) among full-time employees change over time. Overall, the two measures of technological change show a very similar development.[21] Both the average risk of automation and the average RTI among full-time employees have been falling over time. This reflects that the share of workers employed in occupations with high risk of automation and high RTI is falling, possibly due to investments in new automation technologies. This trend could reflect changes both between and within establishments.

As in most other countries in the OECD, Norwegian unions have been on a steady decline during the years of our sample (see Fig. A2 in the Appendix). However, the decline is modest and trade union density still amounted to 36 percent of all private sector employees in 2014, which is high compared to most countries outside Scandinavia. To answer the question of how unions alter the process of technological change, we investigate how structural changes in the occupational composition are affected by changes in union density at the workplace level. In Fig. 4, we illustrate how the share of routine workers has evolved within work-

[19] The five composite task measures are: non-routine analytical, non-routine interpersonal, non-routine manual, routine cognitive and routine manual. RTI is calculated as the sum of the routine measures divided by the sum of all measures.

[20] Fig. A1 in the Appendix illustrates how the two different measures to identify routine occupations compare in terms of the average composite task measures. Overall, the average scores are very similar between the two measures.

[21] However, the percentage change in automation risk is larger than in RTI. This partly reflects the construction of the RTI index. The overall variation in the RTI index is 0.25-0.44, while automation risk varies continuously between 0 and 1. While the average risk of automation is reduced from 0.56 to 0.50 between 2002 and 2014, average RTI is reduced from 0.352 to 0.346.

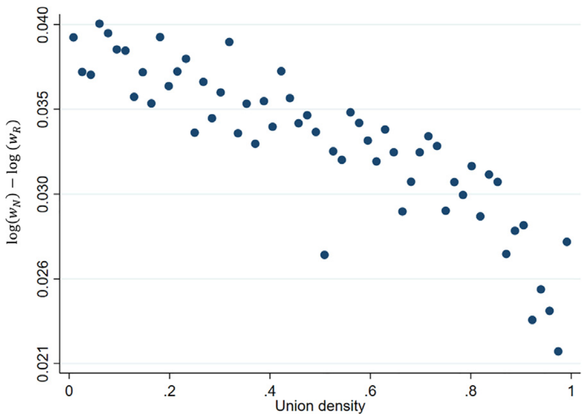

Fig. 5. Binned scatter plot of (log) relative wages between non-routine and routine workers across union density. Note: The binned scatter plot illustrates the average relative wage (in logarithms) between non-routine and routine workers over establishments for different levels of union density. The sample includes all observations of establishments employing at least one worker from each group. N=684,721.

places for different levels of union density, using both the measure of automation risk and RTI. It is apparent from both figures that the share of routine workers has been decreasing at a faster pace in establishments with a strong presence of unions. While the share is reduced by 5 percent from 2003 to 2014 in establishments where the union members make up less than 20 percent of the employees, it is reduced by 20-25 percent in establishments with a union density exceeding 50 percent, depending on which measure we use. The differences may of course be explained by compositional effects, as both union presence and the share of routine workers are higher in some industries than others.

Another question of interest is how relative wages between non-routine and routine workers vary with union density. Fig. 5 shows a binned scatter plot, illustrating the distribution of relative wages across union density within our sample of establishments. The figure shows that non-routine workers, on average, earn higher wages than routine workers for all levels of union density. However, the plot clearly shows a negative relationship between average relative wages and union density. The pattern thus indicates that the average wage gap between non-routine and routine workers is lower in workplaces with strong unions. Although one should be cautious in interpreting the underlying mechanisms that could explain the figures, union wage compression is a plausible explanation of the development illustrated in Fig. 4, where the share of routine workers has been declining faster in more unionized establishments.

5. Results

In this section, we present the results of our empirical analysis. We begin by documenting the relationship between changes in the maximum deduction of union dues and the individual propensity to unionize. We then utilize this source of exogenous variation in two subsequent analyses: How unions affect the relative pay of routine workers over non-routine workers, and how unions alter technological change by influencing the relative demand for routine workers over non-routine workers, *conditional* on the corresponding relative wages.

5.1. Government subsidization of union membership

In Table 1, we document the results from estimating various linear probability models of the individual propensity to unionize as a function of the government tax subsidy of union dues. That is, we estimate variations of the following equation:

$$U_{ikt} = \gamma_0 + \gamma_1 S_{kt} + \gamma_2 ND_{kt} + \boldsymbol{Z}_{it}\xi + \delta_t + u_i + v_k + \theta_{it}, \tag{18}$$

where U_{ikt} is a binary variable equal to 1 if individual i in the hypothetical union k is a union member in year t, and 0 if not. S_{kt} and ND_{kt} denotes the subsidy and net due in NOK 1000 (approximately equal to €88), respectively, in the hypothetical union k in year t. The vector $\boldsymbol{Z}_{it}$ comprises individual workers' characteristics, including education, age, sex, immigration status, and a distinction between part-time and full-time workers. δ_t denotes yearly time dummies, while u_i and v_k denote fixed effects at the individual and union level, respectively. θ_{it} represents random shocks.

Model 1a shows a significant positive relationship between the subsidy and the propensity to join a union. The effect is significantly reduced but still substantial when we control for net union membership fee and various individual characteristics in *Model 1b*. Controlling for individual fixed effects in *Model 1c,* and both individual and union fixed effects in *Model 1d,* [22] further moderates the effect, but the estimated coefficient remains statistically significant. In *Model 1d*, an increase in the subsidy of 1000 NOK is estimated to increase the individual's probability of being a union member by approximately 2 percentage points.[23]

In *Model 1e*, we include a dummy variable measuring whether the individual is occupied in a routine or a non-routine occupation, defined by the associated risk of automation estimated in Frey & Osborne (2017), as well as interactions with the union subsidy and net due. First, we see that workers in routine occupations are associated with a lower probability of being unionized. Second, the positive interaction term indicates that workers in routine occupations are more likely to respond to increases in the tax subsidy compared to workers in non-routine occupations. The findings remain robust when restricting the sample to individuals employed in workplaces with at least ten employees. Overall, we conclude that the tax subsidy appears to be a highly relevant source of exogenous variation in unionization rates.

5.2. Union effect on wages

Results from individual wage regressions are reported in Table 2. *Model 2a* is a standard Mincer earnings equation estimated using ordinary least squares, where we use a second order polynomial in age to proxy experience, while skills are measured by the individual's highest level of education. We further control for sex, and whether or not the individual is an immigrant or works part-time, respectively (see Equation 16). The presence of unions is measured by union density at the workplace level, which is found to be positively correlated with individual earnings. In *Model 2b*, we include an indicator of whether the individual is employed in a routine occupation along with an interaction with union density. The results show that while routine workers on average are paid less than non-routine workers, an increase in workplace union density is estimated to have a larger positive effect on routine wages than non-routine wages. The results do not change much when we include individual fixed effects to control for unobserved heterogeneity in individual productivity in *Model 2c*.

We may suspect that the individual's propensity to join a union will depend on her wage, as well as her attitudes towards unions, which are possibly correlated with unobserved productivity and wages. We therefore instrument union density by exploiting exogenous variation in the government tax subsidy of union dues in *Models 2d.*[24] To control for other changes is the price on union membership, as proposed in Barth et al. (2020), we also include the actual membership fees paid by the individual net of the subsidy in the first-stage equation. We firmly reject the null hypothesis of weak instruments. A ten-percentage point in-

[22] In the construction of the subsidy, we have defined 8,248 hypothetical unions based on occupation by industry cells, see Section 3.3.

[23] When evaluating the marginal effects, we must take into consideration that an increase in the subsidy also reduces the net membership due.

[24] We use the interaction between the routine dummy and the subsidy to instrument R x UD. First-stage results of the interaction term is available upon request.

Table 1
Linear probability models of the impact of subsidizing union membership on individual propensity to join a union

	Model 1a	Model 1b	Model 1c	Model 1d	Model 1e	Model 1f
Subsidy (S)	0.360***	0.073***	0.047***	0.011***	0.009***	0.001
	(154.81)	(27.33)	(20.27)	(4.21)	(3.63)	(0.20)
Net due (ND)		0.050***	0.013***	-0.009***	-0.012***	-0.004***
		(177.37)	(40.19)	(-24.09)	(-26.39)	(-9.09)
Routine (R)					-0.029***	-0.029***
					(-13.90)	(-12.60)
R x S					0.017***	0.017***
					(16.39)	(15.99)
R x ND					0.004***	0.004***
					(7.40)	(7.02)
Year dummies	√	√	√	√	√	√
Controls		√	√	√	√	√
Ind. FE			√	√	√	√
Union FE				√	√	√
Min. empl.						10
N	11,874,008	11,866,919	11,866,919	10,988,908	10,284,019	9,121,160

Note: The endogenous variable is a binary variable equal to 1 if the individual is unionized and 0 otherwise. The subsidy is measured in 1000 NOK (equal to approximately €88) as the marginal tax rate (28 per cent) multiplied with the minimum of actual membership payments and the maximum deductible amount. Controls contains various measures of individual workers' characteristics, including education, age, sex, immigration status, and a distinction between part-time and full-time workers. Sample:2000-2014. Robust standard errors. t statistics in parentheses. *** p<0.001.

crease in union density is estimated to increase the wage of non-routine workers by 1.7 percent, and the wage of routine workers by 3.4 percent. This result remains almost unchanged when restricting the sample to individuals employed in workplaces with at least ten employees in *Model 2e*. The result is also qualitatively robust to the choice of automation measure, although less pronounced when using routine task intensity to distinguish routine and non-routine workers in *Model 2f.* In Table A2 in the Appendix, we arrive at similar results using different thresholds of automation risk to define routine and non-routine occupations, as well as continuous measures of automation risk and RTI, showing that the results are not sensitive to the choice of thresholds. Overall, the results appear to be consistent with the hypothesis from the theoretical model – unions contribute to compress wages between routine and non-routine workers within workplaces.

5.3. Union effect on technological change

The results in the previous section indicate that unions contribute to compress wages between routine and non-routine workers, consistent with the prediction from the theory model in Section 2. We now ask whether unions have any impact on the relative labor demand *conditional* on the relative wage. We thereby shift the unit of analysis from the individual to the workplace. In Table 3, we report results from estimating Equation (17), a relative demand equation, using various estimators and specifications. As a reference point, *Model 3a* is estimated using OLS without any controls but year dummies. The elasticity of substitution between routine and non-routine labor is estimated to be around 2.[25] In other words, if unions raise the wage paid to routine workers by 1 percent relative to the wage of non-routine workers, firms will respond by reducing their relative demand for routine workers by 2 percent. Moreover, the result suggests a negative correlation between union density and the relative demand for routine workers, conditional on relative wages. However, this correlation turns positive when we control for individual workers' characteristics in *Model 3b*.[26] As the OLS-estimates not only reflect the effect of a change in union density *within* establishments, but also unobserved heterogeneity *between* establishments, possibly correlated with union density, the OLS-estimator is likely to be inconsistent. In *Model 3c,* we therefore control for workplace fixed effects. This has the effect of significantly reducing the estimated elasticity of substitution from 2 to 0.5, while the effect of unions is estimated to zero.

While controlling for workplace fixed effects may eliminate the selection bias due to unobserved heterogeneity between workplaces, our estimator is likely to suffer from simultaneity bias as the individual propensity to unionize may be correlated with individuals' occupations. This correlation could be due to different traditions for trade unions in different professions, or the result of technological change (Acemoglu, et al., 2001) or offshoring (Dumont, et al., 2012) influencing unionization rates. To control for this issue of reverse causation, we exploit exogenous variation in the rules for tax deduction of union dues to instrument union density in *Model 3d,* while maintaining the assumption of fixed effects at the workplace level. An increase in workplace union density by one percentage point is now estimated to increase the relative demand for routine workers over non-routine workers by 2.2 percent. The result is statistically significant at the 5 percent level. While the instruments pass conventional tests for weak instruments, we notice that the variation is caused both by changes in the subsidy amount and by changes in the net membership fee.[27] As proposed in Barth et al. (2020), we measure the subsidy relative to the net fee in *Model 3e*. This does not affect the estimated coefficients in any significant way. A ten percent increase in the subsidy ratio is estimated to increase the workplace union density by 1.4 percentage points.

The estimated effect of a change in union density is significantly larger in *Models 3d* and *3e* than what was predicted by the OLS-models. This may indicate that the OLS-estimator is downward biased. However, it is important to emphasize that the IV estimator identifies the local average treatment effect (LATE) among compliers, which in general is not equal to the average treatment effect (ATE). In Section 5.1,

[25] In comparison, the elasticity of substitution between low-skilled and high-skilled workers is usually estimated to be somewhere between 1.4 and 2 (Acemoglu & Autor, 2011, p. 1107).

[26] Characteristics include sex, age, education, and immigration status, all measured as shares at the workplace level.

[27] Recall that the net union membership fee is constructed by subtracting the government subsidy from the gross fee.

Table 2
The effect of unionization on individual earnings

	Model 2a	*Model 2b*	*Model 2c*	*Model 2d*	*Model 2e*	*Model 2f*
Estimator	OLS	OLS	FE	2SLS	2SLS	2SLS
Union density (UD)	0.053***	0.037***	0.043***	0.172***	0.166***	0.215***
	(127.51)	(59.60)	(67.43)	(31.92)	(38.09)	(49.92)
Routine (R)		-0.120***	-0.056***	-0.099***	-0.091***	-0.048***
		(-252.79)	(-125.17)	(-50.84)	(-52.17)	(-28.44)
R *x* UD		0.044***	0.047***	0.165***	0.136***	0.052***
		(55.77)	(60.51)	(34.57)	(34.80)	(13.69)
Age	0.041***	0.038***	0.034***	0.031***	0.033***	0.035***
	(529.80)	(487.89)	(77.88)	(69.79)	(72.01)	(75.71)
Age^2	-0.0004***	-0.0004***	-0.0004***	-0.0004***	-0.0004***	-0.001***
	(-415.74)	(-382.54)	(-424.91)	(-391.87)	(-411.42)	(-414.69)
Medium-skilled	0.095***	0.088***	0.125***	0.122***	0.131***	0.132***
	(344.12)	(303.25)	(191.61)	(187.88)	(183.24)	(185.63)
High-skilled	0.289***	0.265***	0.137***	0.126***	0.133***	0.141***
	(750.35)	(652.98)	(159.13)	(144.99)	(142.23)	(148.54)
Top-skilled	0.484***	0.448***	0.303***	0.287***	0.291***	0.304***
	(861.30)	(748.61)	(219.48)	(205.58)	(201.78)	(205.73)
Part-time worker	-0.122***	-0.104***	0.004***	0.013***	0.017***	0.013***
	(-400.49)	(-329.81)	(12.25)	(37.26)	(49.11)	(36.43)
Immigrant	-0.112***	-0.114***	-	-	-	
	(-274.61)	(-274.75)				
Woman	-0.125***	-0.114***	-	-	-	
	(-499.33)	(-444.75)				
Year dummies	√	√	√	√	√	√
Individual FE.			√	√	√	√
Min. 10 empl. in establ.					√	√
Measure of automation	*Risk*	*Risk*	*Risk*	*Risk*	*Risk*	*RTI*
Subsidy				0.076***	0.082***	0.078***
				(49.85)	(54.37)	(51.23)
Net due				0.033***	0.045***	0.045***
				(121.28)	(157.00)	(159.85)
Cragg-Donald:				30,120.3	48,612.0	45,266.0
Kleibergen-Paap				8,187.7	12,123.6	10,975.1
N	11,873,636	10,873,793	10,873,793	10,398,830	9,226,478	9,226,347

Note: The endogenous variable is log(wage), where wages are measured as total payments per hours, including bonuses and supplementary pay for uncomfortable working hours. Union density (UD) is measured as a rate between 0 and 1. Routine (R) is a dummy variable equal to 1 if the individual is occupied in an occupation with high automation risk and 0 if not. In Models 2a-2e, automation risk is measured according to the categorization in Frey & Osborne (2017). In Model 2f, we use the measure of routine task intensity (RTI) to identify the set of occupations that are in the top employment-weighted third of RTI in year 2000, which is used to proxy high-risk occupations. UD x R denotes the interaction between Routine (R) and Union density (UD). Cragg–Donald and Kleibergen–Paap refer to the Cragg-Donald Wald F statistic and the Kleibergen-Paap Wald rk F statistic of weak instruments, respectively. Sample:2000-2014. Robust standard errors. t statistics in parentheses *** p<0.001.

we found that routine workers are more likely to unionize in response to changes in the rules for tax deduction of union dues than non-routine workers. All else equal, this implies that the expected variation in workplace union density following exogenous variation in the subsidization of union memberships would be higher in workplaces employing a high share of routine workers. The differences between the OLS and IV estimates could thus indicate that changes in tax deductions affect memberships where it matters most for technological change. As suggested in Barth et al. (2020), large effects of changes in union density may reflect threshold effects, as unions may require a collective agreement once the union density reaches certain thresholds.

The results prove robust when we restrict the estimation sample to workplaces present all years to control for firm entry and exit in *Model 3f*. In Table A3 in the Appendix, we also show that the results are robust to how the measure of relative wages is constructed. In *Model 3g*, we test how the results change when we use routine task intensity (RTI) to define routine and non-routine occupations. While both the estimated elasticity of substitution and the estimate of the subsidy ratio in the first-stage equation appear to be invariant to the choice of automation measure, the coefficient on union density is more than doubled when we use RTI to define occupations susceptible to automation. However, while the size of the coefficient is unstable, unions are still estimated to increase the relative demand for routine workers conditional on relative wages. In Table A3 in the Appendix, we also test two alternative thresholds of automation risk to define routine and non-routine occupations. If we increase the threshold value of automation risk that defines routine occupations to 0.8, the positive coefficient is further strengthened, while it turns negative (but not significant) if we lower the threshold to 0.6. This illustrates that the estimated coefficient is sensitive to the choice of threshold value.[28]

When we restrict the sample to workplaces with at least ten employees in *Model 3h*, leaving out almost 60 percent of the workplaces in our sample, the estimated coefficient on union density is no longer statisti-

[28] When we reduce the threshold of automation risk that defines routine occupations to 0.6, the share of routine workers in our sample is increased from 43 percent to 56 percent. When we increase the threshold to 0.8, the share is reduced to 23 percent. This means that even small changes in the threshold value have large consequences for composition of workers in each group. Moreover, the choice of threshold value also alters the composition of workplaces, as only workplaces that employ both routine and non-routine workers are included in the estimation.

Table 3
Union effect on relative demand for routine workers conditional on relative wages

	Model 3a	*Model 3b*	*Model 3c*	*Model 3d*	*Model 3e*	*Model 3f*	*Model 3g*	*Model 3h*
Estimator	*OLS*	*OLS*	*FE*	*2SLS*	*2SLS*	*2SLS*	*2SLS*	*2SLS*
$\log(w_R/w_N)$	-2.029***	-2.057***	-0.471***	-0.516***	-0.526***	-0.557***	-0.557***	-0.853***
	(-201.41)	(-192.81)	(-26.11)	(-22.19)	(-19.43)	(-13.35)	(-26.00)	(-21.80)
Union density (UD)	-0.290***	0.047***	0.003	2.181**	2.656**	3.258*	6.380***	1.740
	(-47.10)	(7.73)	(0.23)	(2.27)	(2.27)	(1.77)	(3.54)	(0.91)
Year dummies	√	√	√	√	√	√	√	√
Controls		√	√	√	√	√	√	√
Workplace FE			√	√	√	√	√	√
Balanced panel						√		
RTI							√	
Min. 10 empl. in establ.								√
First-stage:								
Subsidy				0.027**				
				(2.00)				
Net fee				-0.054***				
				(-4.74)				
Subsidy ratio					0.142***	0.158**	0.150***	0.150**
					(3.86)	(2.37)	(3.44)	(2.49)
Weak instruments test:								
Cragg–Donald:				25.06	19.12	8.88	15.30	10.38
Kleibergen–Paap:				19.67	14.78	6.69	11.09	8.34
3								
No. of workplaces	118,338	118,338	118,338	96,801	96,801	54,862	77,995	39,923
Avg. obs. per workplace	5.8	5.8	5.8	6.8	6.8	8.9	6.8	7.1
Total observations	684,145	684,145	684,145	662,260	662,260	490,323	527,232	282,189

Note: The endogenous variable is $\log(L_R/L_N)$, where the demand for each labor input is measured in hours worked. Wages are measured as market averages of hourly wages within different job classes, determined by occupation and industry. For each individual, the individual's wage is excluded from the average within the job class. Information on whether or not firms participate in collective agreements is used to distinguish unionized from non-unionized firms in construction of the market wages. Controls include sex, age, education, and immigration status, all measured as shares at the workplace level. Union density is measured as a rate between 0 and 1. Models estimated using two-stage least squares (2SLS) use Subsidy and Net fee, or Subsidy ratio as excluded instruments for union density. The tax subsidy is measured in 1000 NOK (equal to approximately €88) as the marginal tax rate (28 per cent) multiplied with the minimum of actual membership payments and the maximum deductible amount). The subsidy ratio measures the subsidy as a share of the net membership fee. Cragg–Donald and Kleibergen–Paap refer to the Cragg-Donald Wald F statistic and the Kleibergen-Paap Wald rk F statistic of weak instruments, respectively. Sample:2003-2014. Robust standard errors. t statistics in parentheses. * $p<0.1$, ** $p<0.05$, *** $p<0.01$

cally significant. This could reflect that the estimated effect of unions on relative conditional labor demand mostly applies to small workplaces, or in industries dominated by small workplaces. Indeed, estimation of *Model 3e* within various industries reveals large heterogeneity in the estimated effects. In Table 4, we show the results within six selected main industries. First, the elasticity of substitution is estimated to 0.6-0.8 within manufacturing, transportation and storage, and commercial services, while it is twice as large within construction and not significantly different from zero within sales and retail and financial services. Second, while unions are estimated to have a positive and significant effect on the relative demand for routine labor within construction and commercial services, we find a negative and significant effect within manufacturing industries. In the other industries, the estimated conditional effect of unions is not significantly different from zero. However, these estimates suffer from weak identification and should not be considered reliable.

6. Conclusion

In this paper, we have investigated how unions alter the process of technological change at the workplace level, as measured by the share of workers employed in routine occupations. We have used both occupational risk of automation and routine task intensity to define routine occupations and shown that the results of our study are robust to the choice of measure. The analysis has been concentrated around how unions alter relative wages between routine workers and non-routine workers, and how unions influence relative labor demand *conditional* on relative wages. In the first part of the analysis, we find that routine workers enjoy a larger union premium compared to non-routine workers, suggesting that unions contribute to increase the relative wage of routine workers over non-routine workers. This finding is consistent with policies of wage compressions followed by many labor unions, as routine workers on average are paid lower wages than non-routine workers.

In response to higher wages, firms reduce their relative demand for routine labor over non-routine labor, as documented in the second part of the analysis. In other words, by increasing the relative wage of workers in occupations with a high risk of being replaced by automation, unions contribute positively to technological change. This echoes the result in Moene & Wallerstein (1997), where wage compression at the national level as a result of centralized bargaining contributes to technological change. Our findings show that similar mechanisms are in place even at the establishment level.

Moreover, we show that unions – conditional on relative wages – influence the employment of routine workers over non-routine workers. This finding gives some support to theories of efficient bargaining, where firms and unions bargain over both wages and employment. An increase in the workplace union density is estimated to increase the relative demand for routine workers over non-routine workers. However, separate estimations for different industries reveal large heterogeneity. Within construction, unions are found to increase the conditional relative demand for routine workers. In other words, by influencing internal relations, unions are found to counteract the positive effect on tech-

Table 4
Union effect on relative demand for routine workers conditional on relative wages within selected industries

	Model 4a	Model 4b	Model 4c	Model 4d	Model 4e	Model 4f
Industry	*Manufacturing*	*Construction*	*Wholesale & retail*	*Transportation & storage*	*Financial activities*	*Commercial services*
$\log(w_R/w_N)$	-0.617***	-1.759***	0.356	-0.780***	-0.235	-0.816***
	(-12.15)	(-30.40)	(0.71)	(-3.96)	(-1.18)	(-8.39)
Union density (UD)	-5.852**	4.065***	-20.880	-5.413	8.695	5.671**
	(-2.29)	(3.24)	(-1.48)	(-0.32)	(1.34)	(2.19)
First-stage:						
Subsidy ratio	0.371***	0.381***	0.144	0.092	0.252	0.294***
	(2.90)	(5.72)	(1.51)	(0.45)	(1.54)	(3.89)
Weak instruments test:						
Cragg–Donald:	16.87	48.72	3.26	0.27	3.15	19.65
Kleibergen–Paap:	8.42	32.67	2.29	0.21	2.37	15.16
No. of workplaces	9,530	12,460	35,932	4,033	1,098	4,366
Avg. obs. per workplace	7.7	6.4	7.2	6.4	5.9	5.3
Total observations	72,948	79,955	257,021	25,995	6,513	23,019

Note: The endogenous variable is $\log(L_R/L_N)$, where the demand for each labor input is measured in hours worked. Wages are measured as market averages of hourly wages within different job classes, determined by occupation and industry. For each individual, the individual's wage is excluded from the average within the job class. Information on whether or not firms participate in collective agreements is used to distinguish unionized from non-unionized firms in construction of the market wages. Union density is measured as a rate between 0 and 1. All models are estimated using 2SLS with workplace fixed effects, yearly time dummies and controls on workers' sex, age, education, and immigration status (measured as shares at the workplace level). The subsidy ratio is used as excluded instrument for union density. The subsidy is defined as the marginal tax rate (28 per cent) multiplied with the minimum of actual membership payments and the maximum deductible amount). The subsidy ratio measures the subsidy as a share of the net membership fee. Cragg–Donald and Kleibergen–Paap refer to the Cragg-Donald Wald F statistic and the Kleibergen-Paap Wald rk F statistic of weak instruments, respectively. Sample:2003-2014. Robust standard errors. t statistics in parentheses. * $p<0.1$, ** $p<0.05$, *** $p<0.01$

nological change that we establish through the wage channel. Within manufacturing industries, however, unions are found to reduce the conditional relative demand for routine workers, thereby reinforcing the estimated positive influence of unions on technological change.

Heterogeneity across industries may reflect different union policies and experience with technological change. Indeed, both union density and collective bargaining coverage are significantly higher within manufacturing than in the construction industry. Norwegian manufacturing firms are also highly exposed to international competition and may thus be dependent of investments in new productive technology in order to stay is business. The construction industry, on the other hand, primarily serves the domestic market but has witnessed a decline in labor productivity due to massive labor migration following the expansions of the European Union in 2004 and 2007. Such differences in market conditions may influence how trade unions perceive investments in new technology.

We contribute to the literature on the interactions between trade unions and technological change by empirically identifying two mechanisms through which unions may influence automation decisions at the workplace level. However, our results rely on the use of observed structural changes in occupational compositions as a proxy for technological change. These changes could also reflect trends in offshoring or outsourcing of certain tasks, improvements in enabling technologies, organizational innovations, or supply side effects. Moreover, both measures used to evaluate occupations are constant over time. Future studies on unions and technological change should consider the use of time-varying classification of occupations to capture how unions may not only influence the composition of occupations, but also the composition of tasks within occupations.

Data Availability Statement

The data that support the findings of this study are available from Statistics Norway. Restrictions apply to the availability of these data, which were used under license for this study. Researchers affiliated with an approved research institution, or a public authority can apply to data from Statistics Norway (https://www.ssb.no/en/data-til-forskning/utlan-av-data-til-forskere).

Declaration of Competing Interest

none.

Data availability

The authors do not have permission to share data.

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Appendix

A1. Descriptive statistics

Table A1

Table A1
Descriptive statistics at the workplace level. 2003-2014.

NACE A38	Industry	Union density	Collective agreement coverage	Mean risk of automation	Mean RTI	Share of high-risk workers	Share of high RTI workers	N
A	Primary	15 %	8 %	0.63	0.34	58 %	14 %	83 079
B	Mining and quarrying	33 %	35 %	0.56	0.35	40 %	28 %	9 493
C	Manufacturing	25 %	32 %	0.60	0.36	48 %	55 %	156 329
D-E	Technical infrastructure	55 %	26 %	0.51	0.35	25 %	36 %	18 037
F	Construction	13 %	13 %	0.59	0.34	38 %	21 %	238 660
G	Wholesale and retail	16 %	16 %	0.60	0.34	61 %	12 %	587 950
H	Transportation and storage	23 %	11 %	0.55	0.36	16 %	46 %	136 831
I	Hotel and restaurants	15 %	16 %	0.68	0.36	59 %	56 %	98 349
J	ICT	23 %	11 %	0.34	0.34	23 %	9 %	78 605
K	Finance	54 %	55 %	0.46	0.33	8 %	7 %	35 564
L-M	Professional services	21 %	7 %	0.48	0.34	31 %	35 %	255 349
N	Commercial services	17 %	13 %	0.53	0.35	28 %	32 %	79 148
O	Public adm. and defense	75 %	28 %	0.41	0.33	17 %	17 %	163
P-Q	Education and health care	36 %	8 %	0.29	0.33	9 %	19 %	168 916
R-S	Cultural activities	23 %	10 %	0.37	0.34	16 %	18 %	122 229
T-U	Other activities	25 %	7 %	0.63	0.36	9 %	74 %	3 201
	Missing	18 %	10 %	0.51	0.34	32 %	26 %	3 317
	Total	21 %	15 %	0.53	0.34	40 %	25 %	2 075 220

Note: All variables are measured at the workplace level (e.g., union density is measured as the mean union density across workplaces – not across workers).

Fig. A1

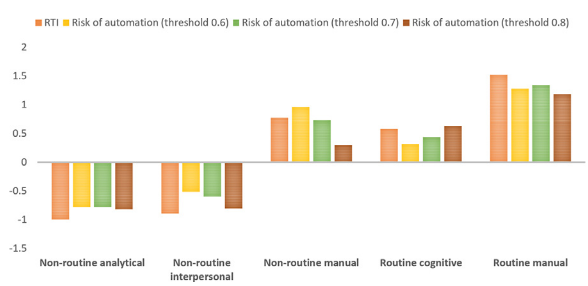

Fig. A1. Average composite task measure scores of routine occupations (demeaned). Note: Average composite task measure scores of routine occupations, with sample mean subtracted, using different definitions of routine occupations. RTI identify routine workers as workers employed in occupations that are in the top employment-weighted third of routine task intensity. The other measures identify routine workers using three different threshold of automation risk.

A2. Supplementary estimation results

Table A2

Table A2
Robustness checks of how unions influence relative wages in routine and non-routine occupations using different automation measures and threshold values

	Model A2a	Model A2b	Model A2c	Model A2d
Estimator	2SLS	2SLS	2SLS	2SLS
Union density (UD)	0.168***	0.224***	0.193***	0.192***
	(36.64)	(56.41)	(29.42)	(6.49)
Routine (R)	-0.096***	-0.050***	-0.119***	-0.756***
	(-50.46)	(-30.39)	(-35.20)	(-21.49)
R *x* UD	0.121***	0.070***	0.079***	0.183**
	(29.04)	(18.88)	(10.45)	(2.33)
Age	0.032***	0.034***	0.033***	0.034***
	(70.92)	(74.80)	(72.07)	(73.60)
Age^2	-0.0004***	-0.0005***	-0.0004***	-0.0004***
	(-403.66)	(-414.48)	(-407.05)	(-408.45)
Medium-skilled	0.130***	0.132***	0.132***	0.132***
	(182.93)	(184.58)	(185.72)	(185.62)
High-skilled	0.131***	0.140***	0.134***	0.138***
	(139.88)	(148.28)	(143.60)	(144.81)
Top-skilled	0.287***	0.303***	0.287***	0.295***
	(198.70)	(206.63)	(198.51)	(198.77)
Part-time worker	0.018***	0.013***	0.017***	0.015***
	(51.53)	(38.67)	(48.27)	(41.72)
Measure of automation	*Risk*	*Risk*	*Risk*	*RTI*
Threshold	*0.6*	*0.8*	*Continuous*	*Continuous*
Subsidy	0.089***	0.084***	0.093***	0.171***
	(58.62)	(55.61)	(58.70)	(45.95)
Net due	0.044***	0.049***	0.033***	-0.127***
	(146.35)	(176.93)	(88.45)	(-59.32)
Cragg-Donald:	54,328.6	48,938.4	47,103.5	42,208.9
Kleibergen-Paap	12,536.0	12,568.6	9,197.0	9,107.1
N	9,226,478	9,226,478	9,226,478	9,226,347

Note: The endogenous variable is log(wage), where wages are measured as total payments per hours, including bonuses and supplementary pay for uncomfortable working hours. Union density (UD) is measured as a rate between 0 and 1. All models include year dummies and individual fixed effects. In Models A1a and A1b, Routine (R) is a dummy variable equal to 1 if the individual is occupied in an occupation with a risk of automation equal to or above the specified threshold. In Models A1c and A1d, Routine (R) is measured as a continuous variable using estimated risk of automation from Frey & Osborne (2017) and routine task intensity, respectively. Cragg–Donald and Kleibergen–Paap refer to the Cragg-Donald Wald F-statistic and the Kleibergen-Paap Wald rk F- statistic of weak instruments, respectively. UD x R denotes the interaction between Routine (R) and Union density (UD). Sample:2000-2014. Robust standard errors. t statistics in parentheses * p<0.1, ** p<0.05, *** p<0.01.

Table A3

Table A3
Robustness checks of how unions influence relative demand for routine over non-routine labor using different threshold values and wage measures

	Model 3e	Model A3a	Model A3b	Model A3c	Model A3d
Estimator	*2SLS*	*2SLS*	*2SLS*	*2SLS*	*2SLS*
$\log(w_R/w_N)$	-0.526***	-0.459***	-0.567***	-0.596***	-0.295***
	(-19.43)	(-33.17)	(-16.81)	(-22.41)	(-19.99)
Union density (UD)	2.656**	-1.376	7.484***	2.382**	4.259***
	(2.27)	(-1.63)	(3.08)	(2.09)	(3.26)
Risk threshold	0.7	0.6	0.8	0.7	0.7
Wage measure	Market wages controlling for collective agreements	Market wages controlling for collective agreements	Market wages controlling for collective agreements	Market wages	Actual wages
First-stage:					
Subsidy ratio	0.142***	0.197***	0.133***	0.143***	0.138***
	(3.86)	(5.13)	(2.82)	(3.89)	(3.84)
Weak instruments test:					
Cragg–Donald:	19.12	28.59	10.97	19.36	20.37
Kleibergen–Paap:	14.78	21.09	7.93	14.96	15.99
No. of workplaces	96,801	97,563	64,262	96,801	100,615
Avg. obs. per workplace	6.8	6.8	6.7	6.8	6.8
Total observations	662,260	666,813	430,048	662,260	681,114

Note: The endogenous variable is $log(L_R/L_N)$, where the demand for each labor input is measured in hours worked. Wages are measured as market averages of hourly wages within different job classes, determined by occupation and industry. For each individual, the individual's wage is excluded from the average within the job class. Information on whether or not firms participate in collective agreements is used to distinguish unionized from non-unionized firms in construction of the market wages. All models include year dummies, workplace fixed effects and controls on sex, age, education, and immigration status (measured as shares at the workplace level). Union density is measured as a rate between 0 and 1. Models estimated using two-stage least squares (2SLS) use Subsidy and Net fee, or Subsidy ratio as excluded instruments for union density. The tax subsidy is measured in 1000 NOK (equal to approximately €88) as the marginal tax rate (28 per cent) multiplied with the minimum of actual membership payments and the maximum deductible amount). The subsidy ratio measures the government tax subsidy on union membership as a share of the net membership fee. Cragg–Donald and Kleibergen–Paap refer to the Cragg-Donald Wald F statistic and the Kleibergen-Paap Wald rk F statistic of weak instruments, respectively. Sample:2003-2014. Robust standard errors. t statistics in parentheses. * p<0.1, ** p<0.05, *** p<0.01

A3. Overview of the Norwegian institutional context

The relationship between employers and employees in Norway is organized through an interaction between legislation and collective agreements, where the importance of the latter is high compared to other countries. The labor market is characterized by strong trade unions and employer's associations. During our sample period, trade union density in the private sector has declined steadily but modestly from 40 percent in 2002 to 36 percent in 2014. However, union density and among Norwegian workers remain among the highest in the OECD.[29] The same applies to the coverage rate of collective bargaining, though the coverage rate is lower than in many other Western European countries, where collective agreements at sectoral level may be required by law to extend to all firms and workers irrespective of union membership.[30]

In contrast to many other European countries, there is no general minimum wage in Norway. Instead, minimum wages are determined by collective agreements. Collective bargaining in Norway has a clear hierarchical structure. As in several other Western European countries, wages in the private sector may be negotiated at three levels: central, sectoral, and local. At the national level, a few major confederations determine the content of the basic agreements. The basic agreements form the basis for all lower-level agreements in specific industries. The second level in the hierarchy consists of agreements for specific industries, often referred to as business sector agreements. Local agreements between employers and employee representatives at company level, which are adapted to local conditions, make up the third level of the bargaining hierarchy. In contrast to sectoral agreements, local agreements automatically extend to all workers in occupations covered by the agreement, irrespective of union membership. Collective agreement coverage in Norway thus depends on the existence of local agreements. In general, if the union density among workers within the same bargaining area in a firm is above a certain threshold, the union will demand a collective agreement.[31] If the employer is organized in an employer's association, the agreement will be ratified more or less automatically. If the employer is not organized, the trade union will enter a direct agreement with the employer – if necessary, through the use of industrial action.

[29] See the dataset on 'Trade Unions and Collective Bargaining' in the OECD statistical database.

[30] This is the case in Austria, Belgium, Finland, France, Germany, the Netherlands, and Portugal (García-Serrano 2009). A comprehensive overview of the prevalence and functioning of collective agreements in the OECD, including differences in the practice of *ergo omnes* clauses and extensions are found in the OECD report "Negotiating Our Way Up" (2019)

[31] The premise of a threshold in the union membership rate is institutionalized in the Basic Agreement between the Confederation of Norwegian Enterprise (NHO) and the Norwegian Confederation of Trade Unions (LO) (Hovedavtalen § 3-7, nr. 2). This states that employees cannot require that the enterprise become part of a collective agreement without at least 10 per cent of the employees being members of a union.

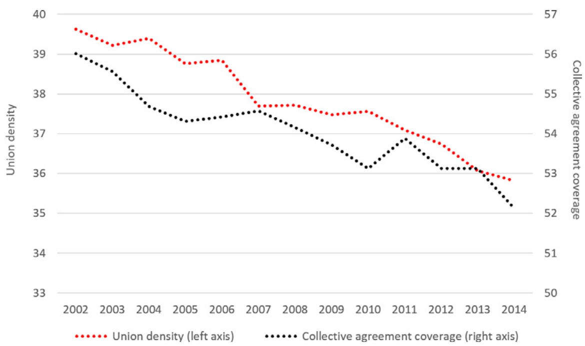

Fig. A2. Average union density (left axis) and collective agreement coverage rate (right axis)

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