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ABSTRACT

Robots and Worker Voice: An Empirical Exploration*

The interplay between labour institutions and the adoption of automation technologies remains poorly understood. Specifically, there is little evidence on how the nature of industrial relations shapes technological choices at the workplace level. Using a large sample of more than 20000 European establishments located in 28 countries, this paper documents conditional correlations between the presence of employee representation (ER) and the use of automation technologies. We find that ER is positively associated with robot usage. The presence of ER also correlates with the utilization of software-based artificial intelligence tools for data analytics. We extensively dig into the mechanisms through which ER may foster the use of robots by exploiting rich information on the *de facto* role played by ER bodies in relation to well-defined decision areas of management. Greater automation in establishments with ER does not seem to result from more adversarial employment relationships (as measured by past strike activity) or constraints on labour flexibility imposed by the interference of employee representatives with dismissal procedures. Interestingly, the positive effect of ER on robot usage is driven by workplaces operating in relatively centralized wage-setting environments, where one would expected a more limited influence of ER on wages. While our findings are exploratory and do not have a causal interpretation, they are suggestive that ER influences certain workplace practices, such as skill development, job redesign and working time management, that may be complementary to new automation technologies.

JEL Classification: J50, O32, O33

Keywords: automation, robots, artificial intelligence, unions, employee representation, labor market institutions, European Company Survey

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1 Introduction

Automation technologies, such as robots and artificial intelligence, have significantly improved in recent years (Haenlein and Kaplan, 2019) and have found wide applications in many industries (e.g., Acemoglu and Restrepo, 2020; Graetz and Michaels, 2018a). Such trends have been widely investigated in the literature, especially with reference to their potential implications for labor displacement (Brynjolfsson and McAfee, 2014; Autor, 2015; Ford, 2015; Susskind and Susskind, 2015; Goos, 2014). In relation to this point, some scholars have raised concerns about the spread of "so-so technologies" that replace workers but generate very small productivity gains (Acemoglu and Restrepo, 2019b).

Much less attention, however, has been paid to the factors that drive the choice of automation in the first place. Recently, some authors have raised interest about the role that labour market institutions can play in relation to new technologies (e.g. see Presidente, 2020; Acemoglu and Restrepo, 2019b). Yet, in these contributions the effects of such institutions remain a black-box. Does the nature and composition of firm-level industrial relations affect automation? Which are the mechanisms through which this effect takes place?

This paper begins to address these questions by investigating if and how the choice to introduce robotization is influenced by the presence of workplace employee representation (ER), i.e. an institutional channel for employee voice through which workers exert an influence on work organization and employment-related issues as exists in many European countries (e.g. unions, works councils, consultative committees). Although the conflicting nature of automation technologies is often emphasized (see, e.g. Spencer and Slater, 2020; Freeman, 2020), there is still a dearth of evidence on the relationship between labour-friendly institutions, such as ER, and the adoption of robotics at the firm level. Exploring this relationship can provide new insights about the features of workplace governance and industrial relations structures that are best suited to foster production technology upgrading and help firms to internalize the external costs created by their technological choices by directing the selection of new technologies toward those involving large productivity gains and away from so-so technologies(Autor et al., 2020).

From a theoretical point of view, ER can affect investments in automation through different channels. First, ER can affect automation via higher wages, which provide incentives to substitute labour with capital. In this case the association between ER and automation would be positive. Alternatively, ER can affect automation via hold-up, namely the possibility that granting workers control rights rises their bargaining power and thereby discourages capital formation (Grout, 1984). Such mechanism would thus predict a negative association between ER and automation. Finally, ER can influence automation through non-wage aspects of labour, such employment rigidity, power relations and job design. In particular, the more ER leads to rigid and conflicting employment relationships, and the more it favors job designs that allow for the replacement of unhealthy and unpleasant tasks, the more ER will be positively associated with automation. Although hold-up is the only mechanism predicting a negative relationship between ER and automation, different features of the employment relation can be used to discriminate among the others channels.

We investigate the empirical relevance of each mechanism by using unique establishment-level data from the last wave of the European Company Survey (2019), which cover more than 21,000 workplaces located in 28 countries and provide harmonized information on the presence of ER bodies, automation technologies and a wide range of management practices. Specifically, this survey includes questions on whether the establishment uses robots as well as other type of software-based AI. Moreover, the survey reports detailed information about the ER structure alongside a large set of other establishment-level characteristics, such as: employment trends, dismissals, strikes, working time arrangements, and task complexity. The availability of such a wealth of information allows us to disentangle among the mechanisms driving the relationship between ER and investments in automation.

Our econometric analysis reveals a positive and statistically significant association between ER and both the use of robots and digital tools for data analytics, which is robust in a battery of alternative Linear Probability Model (LPM) specifications. We account for the potential endogeneity of ER bodies by exploiting firm coverage by higher-level wage agreements as an exogenous factor that shifts the probability of organizing ER structures at the workplace level. Our instrumental variable (IV) estimates reinforce our main findings.

Finally, we explore the plausibility of alternative theoretical mechanisms proposed in the literature. To do this, we exploit uniquely rich information on the *de facto* influence exerted by employee representatives in relation to well-defined decision areas of management. First, the positive correlation between ER and robot usage holds even after controlling for measures of employee influence on the dismissal process at the establishment level. In addition, ER induces more automation in environments characterized by relatively low employment protection. This casts some doubts on the idea that ER may spur automation mainly by interfering with firing decisions and restricting labour flexibility. Second, the association between ER and robots is not channeled by more adversarial employment relationships, as measured by past strike activity. Moreover, the effect of ER on robotization is picked up when we control for measures of employee influence on training, work organization and working time management. Additional estimates show that ER favors automation mainly in establishments located in rapidly ageing countries, where middle age workers are relatively more scarce. Interestingly, the positive effect of ER on robot usage is driven by workplaces operating in highly centralized wage-setting environments, where one would expected a more limited influence of shop-floor employee representation on wages. Taken together, these pieces of evidence suggest that ER may favour automation by improving flexible working time management and facilitating workforce skills upgrading and job redesign. The latter may help to reduce workers' resistance to the introduction of new technologies and optimize their use. More generally, worker voice seems to favor certain workplace practices associated with high-performance work systems that may be complementary to new technologies (Kochan et al., 2020).

Our paper is most closely related to two streams of literature. First, the paper relates to theoretical and empirical works on the relationship between automation and labour (for a review, see Barbieri et al., 2020). The rapid diffusion of AI and robots has led many authors to investigate the effects of these technologies on labour, comparing different dimensions such as employment (Acemoglu and Restrepo, 2020, 2019a; Bessen et al., 2019, 2020; Graetz and Michaels, 2018b; Carbonero et al., 2020; Chiacchio et al., 2018; Dauth et al., 2017), skill polarization (Acemoglu and Restrepo, 2018) and wage inequality (Barth et al., 2020). Rather than focusing on the consequences of automation technologies, we study whether labour market institutions such workplace ER affect their adoption. While some recent studies have began to address similar issues (e.g., Presidente, 2020), they provide only aggregate evidence based on country and/or industry level data. Cheng et al. (2019) use firm-level survey data to investigate the drivers of robot adoption in China but the lack of strong and independent unions prevents them from identifying a direct effect of ER. To our knowledge, this paper provides for the first time direct micro-level evidence on the relationship between ER presence and automation for a large sample of European workplaces.

Secondly, our work integrates the voluminous literature on the effects of ER bodies on capital investments and innovation. Starting from the seminal contribution by Grout (1984), several works have investigated the impact of institutions granting workers control rights on firm investments. While some authors focus primarily on the effect of unionized forms of ER on physical capital formation (Denny and Nickell, 1991; Hirsch, 2004; Machin and Wadhwani, 1991; Cardullo et al., 2015), others extend the analysis to non-unionized forms of ER (Addison et al., 2007) and broaden the spectrum of investments to encompass also intangible capital and R&D (Connolly et al., 1986; Sulis, 2015). In one of the most relevant papers on this topic, Jäger et al. (2019) provides causal evidence that worker participation in firm governance via co-determination rights rises physical capital formation. In this paper we contribute to this literature by studying whether ER affects investments in technologically-advanced capital goods such as robots and software-based AI. Although the latter are likely to become production assets of growing importance in the years to come, a clear understanding of what drives their adoption is still lacking. In this paper we make some first steps in filling this gap.

The remaining of the paper is organized as follows. In Section 2, we discuss the theoretical mechanisms through which employee representation may affect robot and AI utilization. In Section 3, we describe the data and the key variables used in the empirical analysis. In Section 4, we present the results of our econometric study, including the empirical exploration of the possible alternative mechanisms driving the empirical evidence. Section 5 concludes.

2 Theoretical mechanisms

Theoretically, workplace ER can affect automation through various mechanisms.

The most standard channel is the one of automation used by firms to substitute away costly labour. If worker representation institutions push wages up, firms may be induced to adopt automatized capital at a faster rate in more unionized workplaces (Denny and Nickell, 1991). Along these lines, Acemoglu and Restrepo (2019b) report country-level evidence showing that greater unionization rates are associated with higher robots adoption, with the effect being presumably driven by the fact that unions rise labour costs. This view assumes that automation is a form of labour-saving technology and requires robots and workers to be substitute in the production process. The path of progress in automation then depends on the elasticity of substitution between labour and robots. A number of recent studies has explored the employment consequences of automation, either imposing an exogenous technological limit to automation or otherwise concluding in favour of a long-run decline of labour input use, with a labour share eventually reaching zero. In this body of literature, perfect substitution is excluded by Sachs and Kotlikoff (2012), who point to robots as possibly complementary to old generation workers, and Berg et al. (2018), who consider an array of scenarios where the elasticity of substitution is assumed to be finite in most cases. Other works have considered more extreme settings, in which full automation is possible under perfect substitutability between humans and robots, leading to full labour displacement (Sachs et al., 2015; Nordhaus, 2015). Taken together, this labour-saving strand would predict that ER is positively associated with automation, to the extent that ER alters relative input prices by raising wage costs through improved worker bargaining power.

Opposite is the prediction suggested by the perspective looking at industrial relations as informed by the strategic opportunism of unions. In this framework, firms confront an hold-up problem in dealing with ER, which should in turn discourage investments in automation.

In the absence of binding employment contracts, in fact, institutions that give control rights to workers strengthen the worker capacity to *extract rents* (Grout, 1984). Anticipating this, capitalists may reduce investments in automation technologies to avoid a relative large share of quasi-rents stemming from such investments being *ex-post* appropriated by labour. Although several authors recognize that unions can indeed be thought of as rent-extracting institutions (Jensen and Meckling, 1979; Grout, 1984; Lindbeck and Snower, 1989), the empirical evidence on the hold-up hypothesis is mixed. By looking at standard capital goods, several works document a negative effect of unionization on investment (Connolly et al., 1986; Hirsch, 2004), particularly in sunk capital intensive industries (Cardullo et al., 2015), while others find no evidence of holding-up (Machin and Wadhwani, 1991; Card et al., 2014). More directly related to our work, Addison et al. (2007) take into explicit account forms of shop-floor ER, such as work councils, and find that establishments with ER do not have lower investments than those without it. Recently, Jäger et al. (2019) find a positive effects of ER systems based on board representation on firm investments. So far, however, few studies have directly investigated the validity of the hold-up hypothesis with respect to the automation process using firm-level data.

An implicit assumption that allows the application of the hold-up framework to automation-related investments is that robots can be assimilated to any other form of physical capital inputs and are thus vulnerable to similar hold-up problems. This, however, may not be the case. In the standard hold-up story, if capitalists buy machines with firm-specific features, ex-post they can be blackmailed by workers who refuse to operate the machines (knowing they have zero reselling value) unless the capitalists raise their wages. Knowing this, the capitalists may decide not to invest. Yet, if robots can operate by themselves, or at least by involving a much smaller number of employees, the ex-post rent extraction strategy of the workers would be less credible. This may reverse the predictions of the theory. In a recent paper, Presidente (2020) implicitly follows this line of reasoning to explain descriptive industry-level evidence of a positive relationship between labour-friendly institutions and investment in industrial robots. The underlying argument is simple. By shifting bargaining power in favour of workers, labour-friendly institutions rise wages and provide incentives to substitute labour with robots. This effect tends to be disproportionately stronger in sunk-cost intensive industries, where higher vulnerability to hold-up strengthen workers' bargaining power. As a consequence labour-friendly institutions not only induce more automation, but also do so relatively more in industries with more stringent hold-up problems. Obviously, the argument holds under the condition that robots are not exposed to the same risk of hold-up. Otherwise, the stronger bargaining power of workers should discourage capitalists from investing in robotization, as in the standard formulation of the hold-up theory.

Another mechanism through which ER can influence automation is via labour contracts. Fornino and Manera (2019) calibrate a general equilibrium model showing that in presence of demand shock and uninsurable idiosyncratic risks, labour can survive in production even if it is a costlier input than robots as long as employment contracts are sufficiently flexible. The key idea is that such flexibility represents the distinctive comparative advantage of labour, which makes it better suited than robots to cope with macroeconomic shocks. When the latter occur, firms respond by using the most flexible factor, but generally employ both workers and machines. The direct implication of this analysis for our study is that, if strong ER bodies oppose flexible employment (see, e.g. Heery, 2004; Salvatori, 2012; Visser, 2002), the main advantage of labour over robots would disappear and factor substitution should proceed faster. As a result we should expect the presence ER to be associated with positive investments in automation and possibly higher labour displacement.[1]

Among non-wage aspects of ER that can possibly affect automation, an important role can be played also by the interaction between labor conflict and job design. A long tradition of research following the so-called Radical School treats technological choices as socially determined (Gintis, 1976; Braverman, 1974; Marglin, 1974; Bowles, 1985; Skillman, 1988; Duda and Fehr, 1987; Pagano, 1991). In presence of conflicting interests over effort provision between capitalists and workers, it is argued, capitalists may be induced to select the technology on the basis of bargaining power considerations as well as technical efficiency. This implies that one should interpret robots adoption as a response to given power relations, and not only economic convenience. In our context, the Radical approach would suggest that, whenever ER bodies are combined with highly conflicting industrial relations, automation will rise. Robots and software-based AI may indeed represent a suitable tool that capitalists can use to disorganize labour and restore power relations in their favour.[2]

Finally, ER may affect automation choices via its direct effect on job design. In a recent paper, Belloc et al. (2020) follow an institutional complementarities approach (see, e.g. Aoki,

[1]Notice, however, that whether unions oppose flexible employment is controversial. Recent research has showed that unions may favour the employment of a buffer of temporary workers, if this is functional to absorb variations in the labour input use thereby protecting permanent, core workers (Devicienti et al., 2018). ER has been found to increase flexibility also along other margins, such as working-time arrangements (Burdin and Pérotin, 2019).

[2]The argument goes back to Marx: "In England, strikes have regularly given rise to the invention and application of new machines. Machines were, it may be said, the weapon employed by the capitalist to quell the revolt of specialized labour. The self-acting mule, the greatest invention of modern industry, put out of action the spinners who were in revolt." (Marx, 1847). "But machinery does not just act as a superior competitor to the worker, always on the point of making him superfluous (...) It is the most powerful weapon for suppressing strikes, those periodic revolts of the working class against the autocracy of capital."(Marx, 1867). Lazonick (1979) provides a richer and more complex historical account of the interaction between industrial relations and technical changes in the 19th century. More recently, Caprettini and Voth (2020) provide evidence supporting a reverse causal relationship: labour-saving technologies caused social unrest in 1830s England.

2001; Amable, 2000; Landini and Pagano, 2020) and argue that workplace governance and job design (i.e. the task environment workers are involved in) complement each other. In particular, ER supports the emergence of job designs in which the share of automatable tasks is determined more by technical opportunities than by necessity to keep labor discipline in check, targeting in particular the substitution of unhealthy and unpleasant jobs. This may in turn have two effects on the choice of automation. First, it may favour the selection of efficiency-enhancing automation technologies, which at the same time improve working conditions. Second, it may reduce workers' hostility towards automation, allowing for processes of job redesign, upskilling and retraining to take place. Taken together, these two effects suggest that, in presence of ER, high robots and AI adoption can go together with relatively cooperative industrial relations. In line with this view, Gihleb et al. (2020) document that the introduction of robots is indeed associated with significant improvements in industrial workers' health and safety, suggesting that automation can often be a win-win solution for both capitalists and workers.

To sum up, we identify five main mechanisms thorough which ER can affect investments in automation: higher wages, hold-up, employment rigidity, power relations and job design. While the hold-up view predicts a negative association between ER and automation, the remaining four suggest automation to correlate positively with ER. Depending on the mechanism, however, such correlation should be conditional on other features of the employment relationship such as labour market regulation, task composition, and the industrial relations climate. Variation across these dimensions will be exploited in the empirical analysis to discriminate across mechanisms.

3 Data and variables

3.1 The European Company Survey: overview

We test the basic predictions of the model using establishment-level data from the European Company Survey 2019 (van Houten and Russo, 2020). ECS data cover a representative sample of non-agricultural establishments employing at least 10 employees and located across all EU countries. A crucial advantage of this survey is that it provides harmonized cross-country information on employee representation and use of automation technologies. In addition, the survey also reports rich details about management practices and organizational design at the workplace level. The survey is conducted in two steps. The first step involves a telephone interview with a manager, who is asked about establishment characteristics, organizational practices (e.g. compensation policies, working-time arrangements), and industrial relations, including the existence of employee representation structures. The second stage comprises an interview with an employee representative in those establishments in which an employee representation structure is present. The analysis presented in this paper is entirely based on the information gathered in the management questionnaire.

A. Measure of shop-floor employee representation. We focus on institutionalized forms of employee representation. Employee representation is a dummy variable identifying establishments with a trade union, works council or any other country-specific official structure of employee representation (e.g. joint consultative committees). This definition excludes ad-hoc forms of representation and individual employee voice mechanisms.

B. Measure of automation technologies. The survey provides information on establishment-level utilization of automation technologies. Our main measure is a dummy variable equal to 1 if the establishment uses robots, defined in the survey questionnaire as "programmable machines that are capable of carrying out a complex series of actions automatically, which may include the interaction with people". As a validation exercise, Figure 1 plots the correlation between our measure of robot usage and the number of industrial robots (units per 10000 employees) as reported by the International Federation of Robotics (IFR). Both measures are positively correlated. This is reassuring, considering that IFR data on robot density has been extensively used in the literature. In addition, we analyze the association between the presence of ER and the utilization of software-based artificial intelligence. In this case, our proxy is a dummy variable equal to 1 if the establishment use "data analytics to improve the processes of production or service delivery".[3]

C. Other variables. Finally, managers report information on whether the establishment is part of a multi-site firm, establishment size and age, workforce composition (fraction of part-time, permanent employees) and changes in employment in the last three years. There is also information on the fraction of workers performing complex and non-routine tasks. Moreover, managers provide detailed information on whether ER and employees exert *de facto* influence on specific management decisions, such as dismissals, training, work organization, and working time management. Managers also report information on past strike activity and perceived work climate. This rich set of information allows to test for specific mechanisms and control for well-known establishment-level drivers of robot usage.

Descriptive statistics are reported in Table 1. ER is present in about 25% of the establishments in our sample. Roughly 7% of establishments use robots, though these establishments account for 16% of total employment in the sample. The use of robots is higher among establishments with ER (12%). Figure 2 and Figure 3 show there is a positive cross-country correlation

[3]In the questionnaire, "data analytics refers to the use of digital tools for analysing data collected at this establishment or from other sources".

between robot usage and ER incidence considering all establishments and manufacturing establishments respectively. Figure 4 shows the share of establishments using robots by country and workplace ER status. Figure 5 documents robotization across establishments with different characteristics. The larger average robotization under ER seen in the previous figures seems robust across establishments with different age, size, different use of permanent and part-time contracts and facing different levels of market competition and demand predictability.

4 Results

4.1 Employee representation and robot usage

We begin by considering the following baseline regression model:

$$\mathrm{Y}_{ijc} = \beta_0 + \beta_1\,\mathrm{ER}_{ijc} + \mathbf{b}\mathbf{X}_{ijc} + \varepsilon_{ijc} \quad (1)$$

where subscripts i, j and c denote the establishment, industry and country, respectively; Y_{ijc} is a dummy variable equal to 1 if the establishment i in industry j and located in country c uses robots; ER_{ijc} is a dummy variable for the presence of ER at the establishment level; $\mathbf{X}_{ijc}$ is the vector of controls; ε_{ijc} are the residuals. Despite the availability of a rich set of potential control variables, we prefer a parsimonious specification in order to avoid including factors that may also be affected by the presence of ER. In columns (1)-(5) of Table 2, we report the results from estimating a series of Linear Probability Models. In column (1), we estimate a model in which we only include a dummy variable that takes value one for establishments in which there is a ER structure in place and a full set of industry and country dummies. The presence of ER is positively associated with the probability of using robots.

In columns (2)-(5), we sequentially add more controls to see the robustness of the results. In column (2), estimates control for establishment-level differences, including a dummy variable identifying multi-site firms, the age of the establishment and its size as measured by log of the number of employees. In column (3), we also account for differences in workforce composition in terms of the fraction of part-time and permanent workers. In column (4), we additionally control for proxies of the competitive environment faced by establishments, such as competitive pressures and predictability of demand as reported by managers. In column (5), we add a series of "noise controls" on respondents' characteristics (gender and job title of the respondent) in order to increase the precision of our estimates and reduce concerns about measurement error in the organizational variables. The presence of ER is associated with 1.4 percentage point increase in robot usage. Finally, in column (6), we look at the correlation between the presence of ER and the use of software-based artificial intelligence, proxied by the utilization of data analytics. The presence of ER is associated with a 3.8 percentage point increase in the use of data analytics.[4]

One may argue that our results simply reflect the fact that establishments with ER employ an older workforce compared to other establishments. For instance, Acemoglu and Restrepo (2019) show that ageing is associated with greater adoption of robots. Hence, differences in the age structure of the workforce between establishment with and without ER may be an important confounder. Unfortunately, information about the age composition of workplaces was not collected as part of ECS 2019. To mitigate this concern, we proceed as follows. First, we check the age composition of establishments with and without ER using information from ECS 2013. Figure A.1.1 in Appendix does not reveal significant differences in the fraction of workers aged 50+ between the two types of workplaces. Second, we compute the average fraction of workers aged 50+ in size-industry-country cells using data from ECS 2013 and merge this information to each establishment-level observation in ECS 2019. We estimate Equation (1) including workforce age shares. Results remain unchanged (see column (1) of Table A.1.1 in Appendix). Finally, we estimate equation (1) splitting the sample into rapidly-ageing countries countries (above the median in terms of ageing between 1950 and 1990) and slowly-ageing countries. As in Acemoglu and Restrepo (2019), our indicator of ageing is the change in the ratio of older workers (who are above the age of 54) to middle-aged workers (between the ages of 20 and 54) computed from UN Population Statistics. Results from this exercise are presented in column (2)-(3) of Table A.1.1. Interestingly, we find that the effect of ER on robot usage only holds for the subsample of establishments located in rapidly-ageing countries. This suggests that ER facilitates major reorganization of the production process and fosters the use of robots, particularly in environments characterized by the scarcity of middle-age workers.

4.2 Endogeneity

Conditional correlations presented in Table 2 suggests a positive correlation between the presence of ER and the use of new automation technologies. However, we are concerned about the potential endogeneity bias of our estimates. For example, there may be an unobservable variable that is correlated with both robot usage and the presence of ER. To deal with this we consider an instrumental variable (IV) strategy for ER, grounding the identification of a plausible instrument on the analysis of the institutional determinants of unionization.

The costs and benefits of unionization (as well as the propensity and the opportunity to

[4]We obtain qualitatively similar estimates when average marginal effects are obtained from Probit models. Results are available upon request.

organize) are affected by institutional variables such as the centralization of collective bargaining (Schnabel, 2003). Sectoral or regional coverage of collective agreements influences, in particular, the collective action costs needed to establish ER and the benefits that the workers can obtain from it. For instance, when employment conditions are determined by a collective agreement, workers have the incentive to be active proponents of these conditions through union action. Setting up an employee representation structure at the workplace level may also require expert knowledge and operational support which is more likely to be available when there are higher level union confederations involved in collective bargaining (Devicienti et al., 2018). Depending on the labor legislation, it is also possible that sectoral collective agreements cannot be extended to workers if it is absent at the firm an ER body that acts as a signatory party of the agreement. Previous empirical research has showed that the coverage by centralized collective agreements is an important determinant of the degree to which workplace employee representatives can successfully provide benefits and channel employee voice in the workplace. In line with this argument, Scheuer (2011) finds that coverage by a collective agreement actually triples the likelihood of union membership. Moreover, comparative legal analysis clarifies that extension of collective agreements to third parties at the sectoral or regional level is mostly subject to regulatory institutions and labor laws, that are clearly exogenous to the workplace (Adams et al., 2016).

Following these arguments we use information on whether the firm is covered by a collective wage agreement negotiated at the sectoral, regional or national level, i.e. a feature of institutional environment in which the establishments operate, as an exogenous factor that shifts the probability of establishing an ER at the establishment level. Specifically, we build a dummy variable (Higher-level bargaining$_i$) coded 1 if the firm is covered by a higher-level wage agreement and 0 otherwise, and use it as an instrument for ER in Equation (1).

The results are reported in Table 3. Consistent with our priors, the first-stage results show that higher-level collective bargaining coverage is a strong predictor of ER presence at the firm level. Moreover, when entered in the automation regression, the coefficient of the instrumented ER variable has sign and significance coherent with our baseline regressions. We find again that ER positively correlates with robot and data analytics usage. Reassuringly, usual IV diagnostic tests for instrument relevance and exogeneity are passed.[5]

[5] The magnitude of the effect is larger than in the baseline OLS estimates. This could be due to measurement error in our indicator of ER presence. Moreover, OLS estimates could also be downward biased if an omitted determinant of robot usage is negatively correlated with ER presence. For example, new technologies may be associated with an increase in skill polarization (Michaels et al., 2014), which in turn may raise collective action costs associated with the introduction of shared governance mechanisms. In other words, a coalition of highly and low-educated workers may find it more difficult to organize a works council than a coalition of middle-skilled workers.

To understand the economic significance of our results, suppose ER incidence doubles. Given the sample average incidence of 37%, this roughly corresponds to the percentage point difference in ER incidence between UK (14%) and Nordic countries, like Sweden or Denmark (48%). Using column (3) of Table 3, this is associated with a 5.2 percentage points increase in robot usage. This is equivalent in effect to roughly a quarter of the gap in robot usage between manufacturing and retail establishments.[6]

4.3 Mechanisms

Having documented a positive correlation between ER and the use of robots, we now turn to explore the plausibility of different channels discussed in Section 2. Results are presented in Table 4.

First, we analyze whether the presence of ER induces firm owners to introduce robots in response to more adversarial labor-management relationships. We add controls for the occurrence of industrial actions in the last three years (strikes, work-to-rule, or manifestations) and negative work environment. We also interact these variables with the dummy variable indicating the presence of ER.[7] If automation is driven by a more conflictual work environment in establishments with ER, the additional controls should pick up the effect of ER on robot usage. Results are reported in columns (1)-(2) of Table 4. We find little evidence in support of this channel. The effect of ER on automation remains positive and significant even when controlling for proxies of labour-management conflict. There is some evidence that bad work climate negatively correlates with the use of robots.

Second, we analyse whether ER induces greater automation by reducing labour flexibility and hence eliminating the main comparative advantage of labor vis-a-vis robots (Fornino and Manera, 2019). Managers report whether employees directly influenced management decisions on a wide range of areas including dismissals. Indeed, employee representation structures are granted with special prerogatives in relation to dismissals in some European countries[8] and this may restrict the ability of employers to adjust labour. In column (3) of Table 4, we estimate

[6]Similar calculations using column (6) of Table 3 show that moving from UK to Nordic pattern of ER diffusion is associated with a 8.5 percentage points increase in the use of data analytics. This is equivalent to approximately 70% of the conditional gap in the use of data analytics between establishment operating in "very competitive" sectors and establishments operating in "not at all competitive" sectors as reported by managers.

[7]Negative work climate is a dummy variable equal to one if the manager perceives the relation between management and employees to be neither good nor very good. Managers respond to the following question: "How would you describe the relations between management and employees in this establishment in general?"

[8]For example, companies are usually required to inform and consult employee representatives in case of collective redundancies. In Austria, under certain circumstances employers must inform the works council about a planned dismissal, if not the dismissal is unlawful. In companies with more than 20 employees, the works council can legally challenge employer's decision because of the social consequences for the individual employee being dismissed.

Equation (1) including a dummy variable equal to 1 for establishments in which, according to managers, employees exert moderate to great influence on dismissals. We also include this variable interacted with the presence of ER. We find a positive and weakly significant association between employee involvement in the dismissal process and the use of robots. However, the effect of ER on robot usage remains positive and significant, suggesting that other channels might be relevant.[9]

Third, we conduct a similar analysis but controlling for employee influence on other managerial decision areas such training, organization of work, and working time management. Results reported in columns (4)-(6) of Table 4 indicate that employee voice along these dimensions is positively associated with robot usage. More importantly, the inclusion of these variable picks up the effect of ER, which is no longer statistically significant. Hence, once we account for the extent to which employees actually exercise influence on specific managerial domains, an interesting picture emerges. We find suggestive evidence that ER may induce robot usage by facilitating workers' retraining and working time management.[10]

By raising worker bargaining power and wage costs, the presence of ER may induce greater automation through a simple capital-labour substitution mechanism. Unfortunately, information about wages for our sample of establishments is not available. While we do not neglect the potential importance of this conventional channel, indirect evidence suggests that the role of shop-floor employee representation in raising wages could be rather limited. First, estimates reported in column (7) of Table 4 include a dummy variable equal to one for establishments reporting a reduction in employment in the last three years and its interaction with the presence of ER. Although this is a very crude approximation, one would have expected, following the logic of the capital-labour substitution channel, greater automation in establishment with ER that reduced employment compared to establishments without ER. We find, however, that shrinking establishments are less likely to report the use of robots regardless of whether an ER body is present or not.

[9] As an additional exercise, we estimate Equation (1) splitting the sample according to a country-level index of the stringency of employment protection legislation (EPL). If there is some complementary between EPL and ER (e.g. ER may act as shop-floor enforcement mechanism of EPL), one should expect the effect of ER on robot usage to be grater in countries with high EPL. As shown in Table A.1.4, this does not seem to be case. The effect of ER is only present in low EPL subsample.

[10] In the Appendix, we show additional results that are consistent with the evidence presented in this subsection. First, we look at the correlations between the presence of ER and managers' perceptions about the actual influence of employees across different management decision areas (Table A.1.2). The correlation between ER and perceived employee influence on dismissals is not significant. In contrast, the association between ER and perceived employee influence on training and working time management is positive and highly significant. Finally, we look at robot usage exclusively among establishments with ER, but exploiting differences in the extent of ER influence across managerial domains (Table A.1.3). In columns (2)-(5), we show that the influence of ER on training and working time positively correlates with robot usage. In column (1), our estimates indicate that ER-workplaces in which ER bodies exert greater influence on the dismissal process do not significantly differ from other ER-workplaces in terms of robot usage.

In addition, we exploit specific features of European labour market institutions characterized by the coexistence of workplace employee representation and centralized wage-setting systems. One could argue that in more centralized wage settings plant-level wages would be less responsive to the presence of ER as wages are negotiated at a higher level (industry, region or national level). Indeed, theory and some empirical studies suggest employee representatives are less likely to engage in rent extraction activities in workplaces covered by higher-level collective bargaining agreements (Lazear and Freeman, 1995; Hübler and Jirjahn, 2003).[11] We use information reported by managers on whether wages are negotiated at the establishment/company level or at a higher level. We compute the average degree of centralization of the wage-setting process for each industry-country cell. To exploit heterogeneity in collective bargaining coverage, we estimate Equation (1) splitting the sample into establishments operating in low wage centralization (below the median) and high wage centralization settings (above the median). Results reported in Table A.1.5 show that the positive effect of ER on robot usage is restricted to workplaces operating in high wage centralization environments, i.e. settings in which one could expected a more limited influence of workplace ER on wages.

5 Conclusions

Our study sheds light on the interplay between labor institutions and automation technologies. Using establishment level data from 28 European countries, we analyzed the effect of shop-floor employee representation on the use of robots and software-based AI. The wealth of available information allows us compare different theoretical mechanisms underlying this effect.

We found that ER is positively associated with the use of robots. This result is robust also when automation is proxied by the adoption of software-based AI. In the absence of cleaner sources of exogenous variation in employee representation rights, we exploited features of the institutional environment and instrumented ER using firm coverage by sectoral or national wage agreements. Ordinary Least Squares and Instrumental Variables estimates yielded consistent results. This positive association between ER and automation contradicts the predictions based on the hold-up hypothesis. Moreover, additional analysis suggests that neither concerns with adversarial labour-management relationships, nor attempts to remedy to ER-induced labour rigidity drive the more frequent use of robots in establishments with ER results. The lack of information on wages prevent us from investigating the labor cost channel in more detail. However, by using information on establishment-level past employment changes and degree of centralization of wage

[11] Evidence on weaker wage effects of works council in workplaces covered by collective agreements is somewhat mixed (Jirjahn, 2017).

bargaining, we do find some indirect evidence suggesting that robot-labor substitution induced by higher wages is not a primary mechanism behind our main finding. Rather, the most relevant mechanism seems to be that ER leads to job designs in which automation is associated with improved working conditions, e.g. skill upgrading and flexible working time arrangements. This may in turn reduce workers' hostility towards automation and facilitates its introduction. In other words, the presence of ER seems to be coupled with work systems that are complementary to the adoption of new automation technologies.

It is worth acknowledging some limitations of our study. First, the structure of the data does not allow us to obtain a sharp econometric identification. This is a common limitation in most European research on the economic impact of shop-floor employee representation, especially in its unionized form (e.g,. see Devicienti et al., 2018). We are reassured of the validity of our results because a consistent picture emerges when using different estimation strategies. However, further research will have to put the positive association between ER and automation under stricter causal scrutiny. Second, the lack of establishment-level information about labour costs prevents us from gaining direct evidence about the role played by wages in fostering robot-labour substitution. Although the analysis of employment trends suggests such substitution effect is not particularly strong, it cannot be completely ruled out using our data. Finally, longitudinal and more granular information about the feature of investments in robots and AI would allow a much more detailed investigation of the mechanisms driving the effect of ER on automation. In their absence, we must rely only on indirect evidence, which however allows some of the theoretical channels discussed by previous literature to be discarded.

Overall, the results of the paper contributes to contemporary policy discussions in relation to the governance of robots and AI (Goos, 2018; Goldfarb et al., 2019). The growing awareness about the benefits and costs of automation has indeed spurred many academic and public policy debates. In relation to the latter, the paper suggests that alongside labour market policy and social insurance schemes, workplace employee representation is an important component of the governance strategy shaping the future of work. Following our results, by grating employees greater control rights, the automation process cannot only by enhanced, but it can also be redirected towards technologies that can improve both efficiency and working conditions. This evidence points to the need to open a discussion about the most appropriate forms of workplace governance in the age of automation.

References

Acemoglu, D., Restrepo, P., 2018. Low-skill and high-skill automation. Journal of Human Capital 12, 204–232.

Acemoglu, D., Restrepo, P., 2019a. Automation and new tasks: how technology displaces and reinstates labor. Journal of Economic Perspectives 38, 3–30.

Acemoglu, D., Restrepo, P., 2019b. Demographics and automation. MIT Department of Economics Working Paper No. 18-05 .

Acemoglu, D., Restrepo, P., 2020. Robots and jobs: Evidence from US labor markets. Journal of Political Economy 128, 2188–2244.

Adams, Z., Bishop, L., Deakin, S., 2016. CBR Labour Regulation Index (Dataset of 117 Countries). Cambridge: Centre for Business Research.

Addison, J.T., Schank, T., Schnabel, C., Wagner, J., 2007. Do works councils inhibit investment? Industrial and Labor Relations Review 60, 187–203.

Amable, B., 2000. Institutional complementarity and diversity of social systems of innovation and production. Review of International Political Economy 7, 645–687.

Aoki, M., 2001. Toward a Comparative Institutional Analysis. Cambridge, MA: MIT Press.

Autor, D., Mindell, D., Reynolds, E., 2020. The Work of the Future: Shaping Technology and Institutions. Technical Report.

Autor, D.H., 2015. Why are there still so many jobs? The history and future of workplace automation. Journal of Economic Perspectives 29, 3–30.

Barbieri, L., Mussida, C., Piva, M., Vivarelli, M., 2020. Testing the employment and skill impact of new technologies, in: Zimmermann, K.F. (Ed.), Handbook of Labor, Human Resources and Population Economics. New York: Springer.

Barth, E., Roed, M., Schøne, P., Umblijs, J., 2020. How robots change within-firm wage inequality. IZA DP No. 13605 .

Belloc, F., Burdin, G., Cattani, L., Ellis, W., Landini, F., 2020. Coevolution of job automation risk and workplace governance. DEPS WP – University of Siena, no. 841 .

Berg, A., Buffie, E.F., Zanna, L.F., 2018. Should we fear the robot revolution?(The correct answer is yes). Journal of Monetary Economics 97, 117–148.

Bessen, J., Goos, M., Salomons, A., van den Berge, W., 2020. Firm-level automation: evidence from the Netherlands. AEA Papers and Proceedings 110, 389–93.

Bessen, J.E., Goos, M., Salomons, A., Van den Berge, W., 2019. Automatic Reaction - What Happens to Workers at Firms that Automate? Boston Univ. School of Law, Law and Economics Research Paper .

Bowles, S., 1985. The production process in a competitive economy: Walrasian, neo-Hobbesian, and Marxian models. American Economic Review 75, 16–36.

Braverman, H., 1974. Labor and Monopoly Capital. New York: Monthly Review Press.

Brynjolfsson, E., McAfee, A., 2014. The second machine age: Work, progress, and prosperity in a time of brilliant technologies. New York: W. W. Norton & Company.

Burdin, G., Pérotin, V., 2019. Employee representation and flexible working time. Labour Economics 61, 101755.

Caprettini, B., Voth, H.J., 2020. Rage against the machines: Labor-saving technology and unrest in industrializing england. American Economic Review: Insights 2, 305–20.

Carbonero, F., Ernst, E., Weber, E., 2020. Robots worldwide: The impact of automation on employment and trade. IAB-Discussion Paper No. 7/2020 .

Card, D., Devicienti, F., Maida, A., 2014. Rent-sharing, holdup, and wages: Evidence from matched panel data. Review of Economic Studies 81, 84–111.

Cardullo, G., Conti, M., Sulis, G., 2015. Sunk capital, unions and the hold-up problem: Theory and evidence from cross-country sectoral data. European Economic Review 76, 253–274.

Cheng, H., Jia, R., Li, D., Li, H., 2019. The rise of robots in China. Journal of Economic Perspectives 33, 71–88.

Chiacchio, F., Petropoulos, G., Pichler, D., 2018. The impact of industrial robots on EU employment and wages: A local labour market approach. Bruegel Working Paper No. 2 .

Connolly, R.A., Hirsch, B.T., Hirschey, M., 1986. Union rent seeking, intangible capital, and market value of the firm. Review of Economics and Statistics 68, 567–577.

Dauth, W., Findeisen, S., Südekum, J., Woessner, N., 2017. German robots-the impact of industrial robots on workers. CEPR Discussion Paper No. DP12306 .

Denny, K., Nickell, S., 1991. Unions and investment in British manufacturing industry. British Journal of Industrial Relations 29, 113–121.

Devicienti, F., Naticchioni, P., Ricci, A., 2018. Temporary employment, demand volatility, and unions: firm-level evidence. Industrial and Labor Relations Review 71, 174–207.

Duda, H., Fehr, E., 1987. Power, efficiency and profitability: a radical theory of the firm. Economic Analysis 21, 1–26.

Ford, M., 2015. Rise of the Robots: Technology and the Threat of a Jobless Future. New York: Basic Books.

Fornino, M., Manera, A., 2019. Automation and the future of work: Assessing the role of labor flexibility. Mimeo .

Freeman, R.B., 2020. Ownership when AI robots do more of the work and earn more of the income. Journal of Participation and Employee Ownership 1, 74–95.

Gihleb, R., Giuntella, O., Stella, L., Wang, T., 2020. Industrial Robots, Workers' Safety, and Health. IZA Discussion Paper, No. 13672 .

Gintis, H., 1976. The nature of labor exchange and the theory of capitalist production. Review of Radical Political Economics 8, 36–54.

Goldfarb, A., Gans, J., Agrawal, A., 2019. The Economics of Artificial Intelligence: An Agenda. Chicago: University of Chicago Press.

Goos, M., 2014. Explaining job polarization: Routine-biased technological change and offshoring. American Economic Review 104, 2509–26.

Goos, M., 2018. The impact of technological progress on labour markets: policy challenges. Oxford Review of Economic Policy 34, 362–375.

Graetz, G., Michaels, G., 2018a. Robots at Work. Review of Economics and Statistics 100, 753–768.

Graetz, G., Michaels, G., 2018b. Robots at work. Review of Economics and Statistics 100, 753–768.

Grout, P.A., 1984. Investment and wages in the absence of binding contracts: A Nash bargaining approach. Econometrica 52, 449–460.

Haenlein, M., Kaplan, A., 2019. A brief history of artificial intelligence: On the past, present, and future of artificial intelligence. California management review 61, 5–14.

Heery, E., 2004. The trade union response to agency labour in Britain. Industrial Relations Journal 35, 434–450.

Hirsch, B.T., 2004. What do unions do for economic performance? Journal of Labor Research 25, 415–455.

van Houten, G., Russo, G., 2020. European Company Survey 2019 - Workplace practices unlocking employee potential. Technical Report.

Jäger, S., Schoefer, B., Heining, J., 2019. Labor in the boardroom. NBER Working Paper No. w26519.

Jensen, M.C., Meckling, W.H., 1979. Rights and production functions: An application to labor-managed firms and codetermination. Journal of Business 52, 469–506.

Kochan, T., Helper, S., Kowalski, A., Van Reenen, J., 2020. Interdependence of Technology and Work Systems. Technical Report.

Landini, F., Pagano, U., 2020. Stakeholders' conflicts and corporate assets: an institutional meta-complementarities approach. Socio-Economic Review 18, 53–80.

Lindbeck, A., Snower, D.J., 1989. The Insider-Outsider Theory of Employment and Unemployment. Cambridge, MA: MIT Press.

Machin, S., Wadhwani, S., 1991. The effects of unions on investment and innovation: evidence from WIRS. Economic Journal 101, 324–330.

Marglin, S.A., 1974. What do bosses do? The origins and functions of hierarchy in capitalist production. Review of Radical Political Economics 6, 60–112.

Michaels, G., Natraj, A., Van Reenen, J., 2014. Has ict polarized skill demand? evidence from eleven countries over twenty-five years. The Review of Economics and Statistics 96, 60–77.

Nordhaus, W.D., 2015. Are we approaching an economic singularity? Information technology and the future of economic growth. NBER Working Paper No. 21547 .

Pagano, U., 1991. Property rights, asset specificity, and the division of labour under alternative capitalist relations. Cambridge Journal of Economics 15, 315–342.

Presidente, G., 2020. Institutions, Holdup and Automation. CESifo Working Paper No. 7834 .

Sachs, J.D., Benzell, S.G., LaGarda, G., 2015. Robots: Curse or blessing? A basic framework. NBER Working Paper No. 21091 .

Sachs, J.D., Kotlikoff, L.J., 2012. Smart machines and long-term misery. NBER Working Paper No. 18629 .

Salvatori, A., 2012. Union threat and non-union employment: A natural experiment on the use of temporary employment in British firms. Labour Economics 19, 944–956.

Scheuer, S., 2011. Union membership variation in Europe: a ten-country comparative analysis. European Journal of Industrial Relations 17, 57–73.

Schnabel, C., 2003. Determinants of trade union membership, in: Addison, J.T., Schnabel, C. (Eds.), International Handbook of Trade Unions. Cheltenham: Edward Elgar, pp. 13–44.

Skillman, G., 1988. Bargaining and replacement in capitalist firms. Review of Radical Political Economics 20, 177–183.

Spencer, D., Slater, G., 2020. No automation please, we're British: technology and the prospects for work. Cambridge Journal of Regions, Economy and Society 13, 117–134.

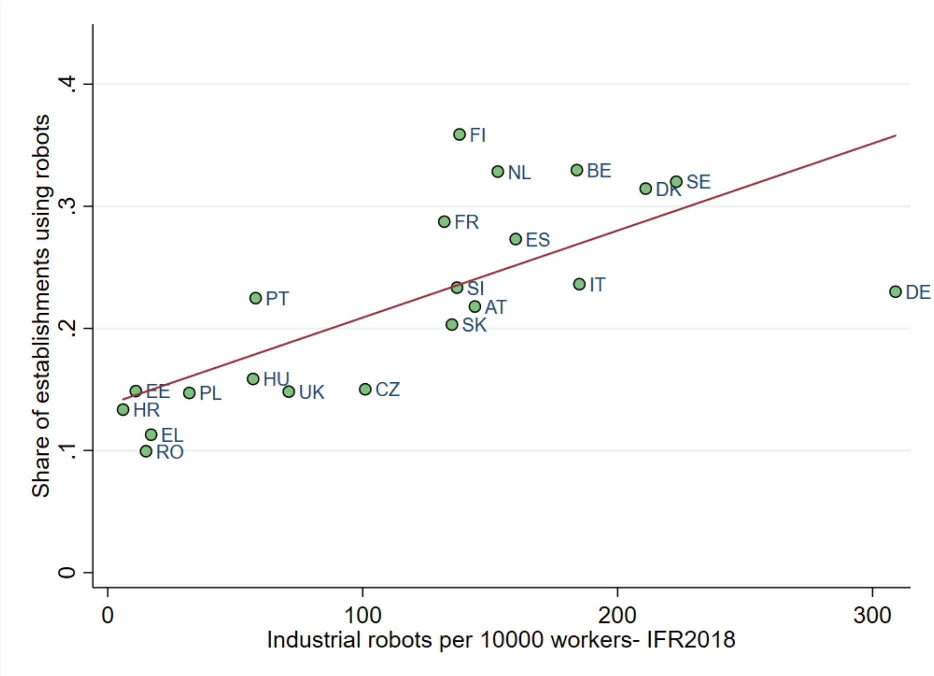
Sulis, G., 2015. Unions and investment in intangible capital. IZA World of Labor .

Susskind, R.E., Susskind, D., 2015. The Future of the Professions: How Technology Will Transform the Work of Human Experts. Oxford: Oxford University Press.

Visser, J., 2002. The first part-time economy in the world: a model to be followed? Journal of European Social Policy 12, 23–42.

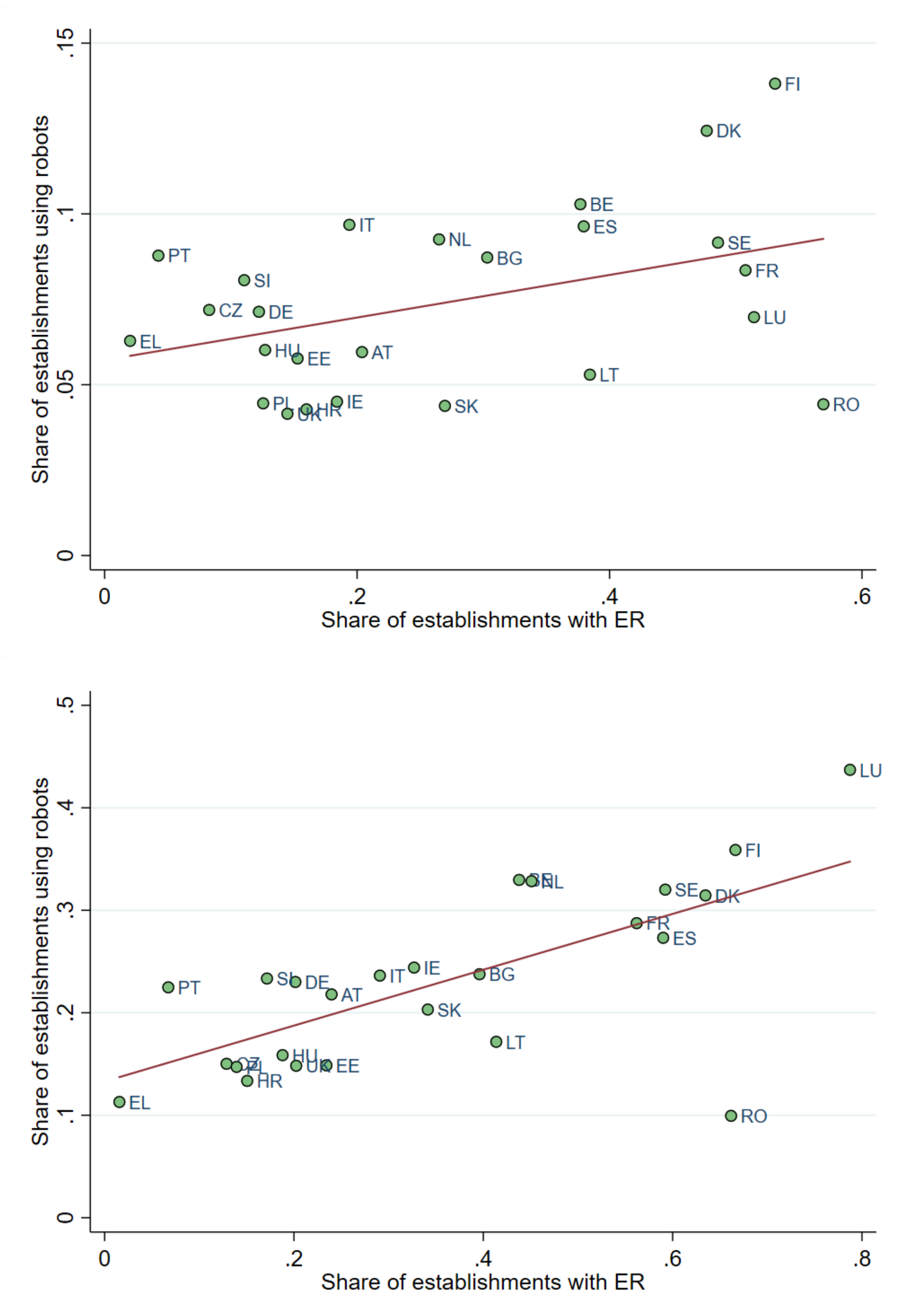
Figures and Tables

Figure 1: Robot usage and robot density (IFR 2018) in Manufacturing



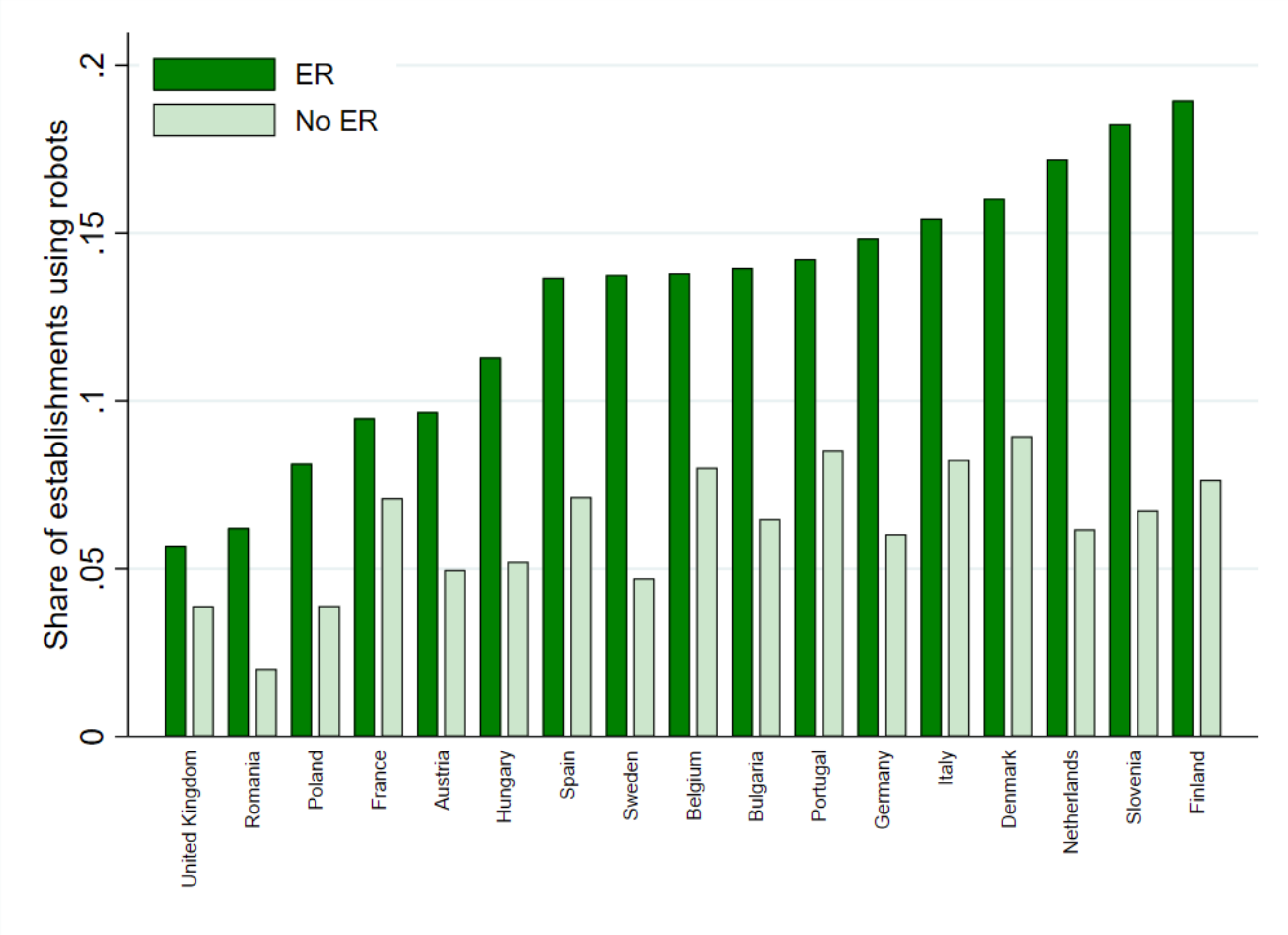
Notes: Pooled data from the European Company Survey 2019. Observations from Malta, Cyprus and Latvia excluded due to low number of cases. Robot usage refers to establishments using "programmable machines that are capable of carrying out a complex series of actions automatically." Robot density is the number of industrial robots per 10000 workers (source: International Federation of Robotics 2018),

Figure 2: Robot usage and ER. All sectors (top) and Manufacturing (bottom)



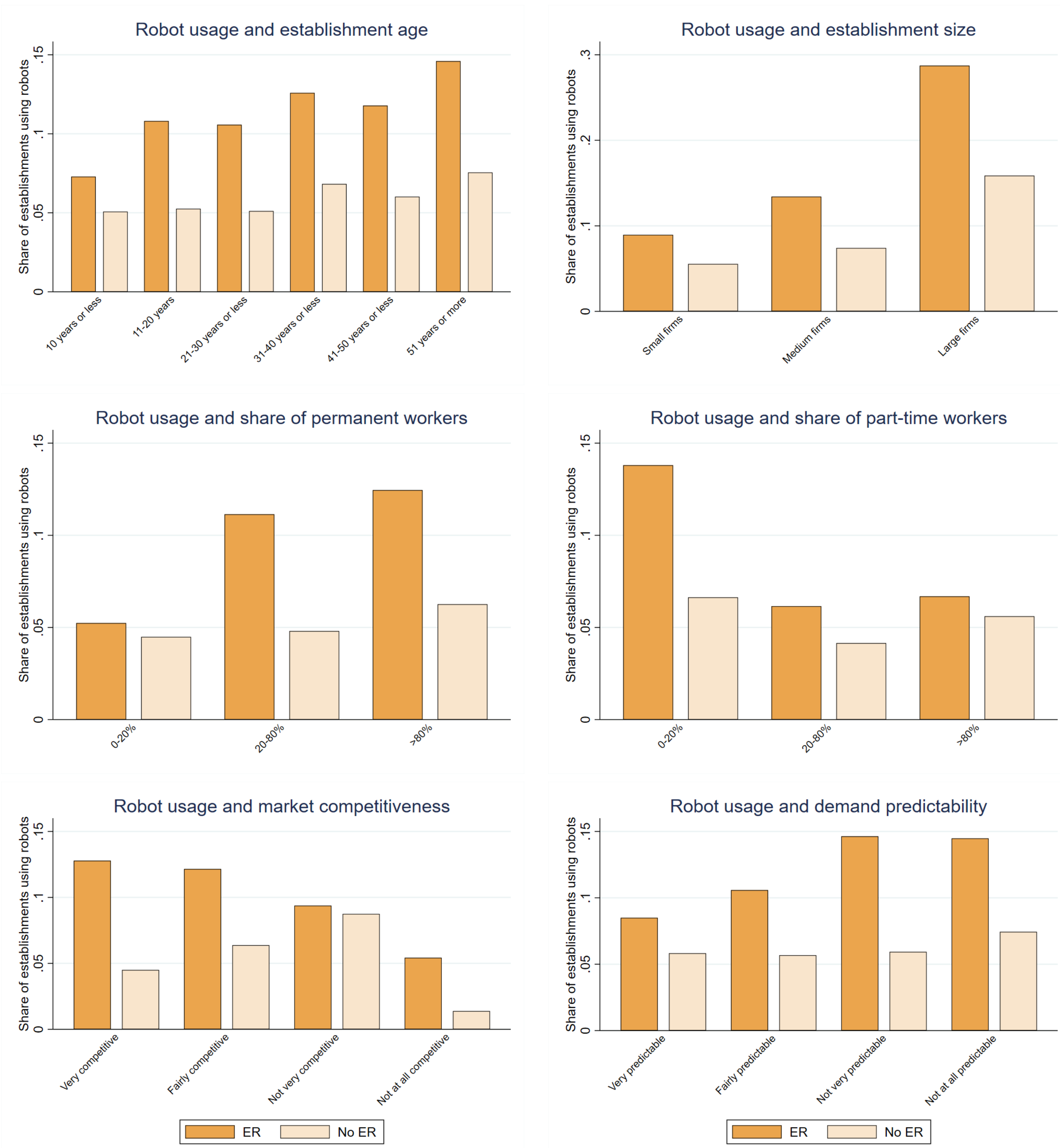
Notes: Pooled data from the European Company Survey 2019. Observations from Malta, Cyprus and Latvia excluded due to low number of cases. Sample weights are used. Robot usage refers to establishments using "programmable machines that are capable of carrying out a complex series of actions automatically."

Figure 3: Robot usage by workplace ER status in selected countries



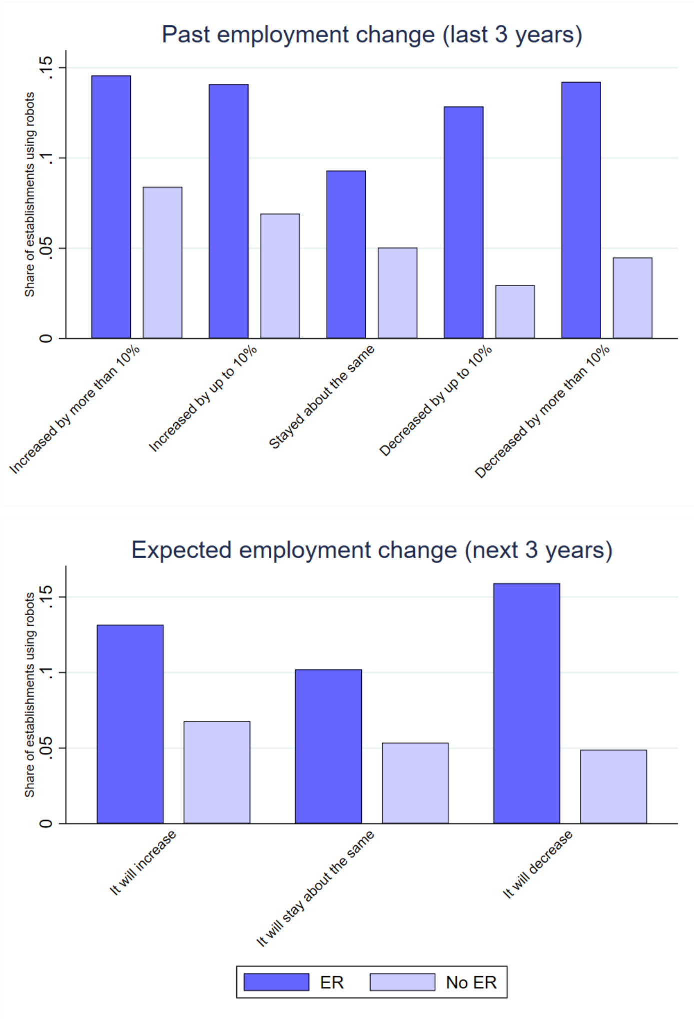
Notes: Pooled data from the European Company Survey 2019. Sample weights are used. Robot usage refers to establishments using "programmable machines that are capable of carrying out a complex series of actions automatically."

Figure 4: Use of robots and establishment characteristics



Notes: Pooled data from the European Company Survey 2019. Sample weights are used. Robot usage refers to establishments using "programmable machines that are capable of carrying out a complex series of actions automatically."

Figure 5: Robot usage and employment change



Notes: Pooled data from the European Company Survey 2019. Sample weights are used. Robot usage refers to establishments using "programmable machines that are capable of carrying out a complex series of actions automatically."

Table 1: Main variables' description and descriptive statistics

Variables	Description as in the ECS questionnaire	Mean	Std.Dev.
ER	An official employee representation currently exists in the establishment (yes/no)	0.246	0.431
Use of robots	Machines carrying out complex actions automatically are used (yes/no)	0.073	0.261
Data analytics	Digital tools for analysing data to improve production or service delivery are used (yes/no)	0.449	0.497
Plant size	Number of employees (log.)	3.292	0.842
Plant age	Years since the establishment has been carrying out its activity	35.207	35.047
Multi-site	This is one of more establishments belonging to the same company (yes/no)	0.243	0.429
Permanent workers <20%	Employees in the establishment with an open-ended contract are < 20% (yes/no)	0.081	0.273
Permanent workers 20-80%	Employees in the establishment with an open-ended contract are 20-80% (yes/no)	0.146	0.353
Permanent workers >80%	Employees in the establishment with an open-ended contract are > 80% (yes/no)	0.760	0.426
Part-time workers <20%	Employees in the establishment working part-time are < 20% (yes/no)	0.670	0.470
Part-time workers 20-80%	Employees in the establishment working part-time are 20-80% (yes/no)	0.260	0.438
Part-time workers >80%	Employees in the establishment working part-time are > 80% (yes/no)	0.053	0.224
Market competition: high	The market for the main product/service is very competitive (yes/no)	0.355	0.478
Market competition: med	The market for the main product/service is fairly competitive (yes/no)	0.498	0.499
Market competition: low	The market for the main product/service is not very competitive (yes/no)	0.104	0.305
Market competition: null	The market for the main product/service is not competitive at all (yes/no)	0.029	0.170
Market uncertainty: high	The market for the main product/service is not predictable at all (yes/no)	0.041	0.200
Market uncertainty: med	The demand for the main product/service is not very predictable (yes/no)	0.287	0.452
Market uncertainty: low	The demand for the main product/service is fairly predictable (yes/no)	0.571	0.494
Market uncertainty: null	The demand for the main product/service is very predictable (yes/no)	0.077	0.267
Manager gender	The manager answering to the questionnaire is a woman	0.518	0.499
Manager position: general	Position held by the manager: general manager (yes/no)	0.183	0.387
Manager position: owner	Position held by the manager: owner-manager (yes/no)	0.205	0.403
Manager position: HR	Position held by the manager: human-resource manager, personnel manager (yes/no)	0.184	0.388
Manager position: training	Position held by the manager: training manager (yes/no)	0.003	0.058
Manager position: finance	Position held by the manager: finance/accounting manager (yes/no)	0.169	0.375
Manager position: other	Position held by the manager: other (yes/no)	0.244	0.429

Notes: Pooled data from the European Company Survey 2019. Sample weights are used.

Table 2: Use of robots and ER

Variables	(1) Use of robots	(2) Use of robots	(3) Use of robots	(4) Use of robots	(5) Use of robots	(6) Data analytics
ER	0.069***	0.016***	0.014***	0.015***	0.014**	0.038***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.008)
Observations	20,295	20,035	19,595	19,176	19,106	20,452
R-squared	0.138	0.167	0.170	0.169	0.170	0.132
Country + industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
Establishment-level controls	No	Yes	Yes	Yes	Yes	Yes
Workforce composition	No	No	Yes	Yes	Yes	Yes
Competitive/Uncertain environment	No	No	No	Yes	Yes	Yes
Manager's controls	No	No	No	No	Yes	Yes

Notes: Estimates obtained from LPM models with robust standard errors in parentheses. In columns 1-5, the dependent variable is a dummy variable indicating whether the establishment uses robots, i.e. programmable machines that are capable of carrying out a complex series of actions automatically. In column 6, the dependent variable is a dummy variable indicating whether the establishment uses data analytics to improve the processes of production or service delivery, where data analytics refers to the use of digital tools for analysing data collected at this establishment or from other sources. Establishment-level controls: plant size, plant age, multi-site. Workforce composition: % permanent contracts, % part-time workers. Competitive/uncertain environment: predictability of demand and competitive pressures as perceived by the manager. Manager's characteristics (gender, position). *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Use of robots and ER: IV estimates

Variables	(1) ER (First stage)	(2) Use of robots (Reduced form)	(3) Use of robots (Second stage)	(4) ER (First stage)	(5) Data analytics (Reduced form)	(6) Data analytics (Second stage)
ER			0.149*			0.232*
			(0.077)			(0.121)
Higher level bargaining	0.078***	0.012*		0.076***	0.018*	
	(0.008)	(0.006)		(0.007)	(0.009)	
First-stage diagnostics:						
[Cragg-Donald stat. p-value]	[0.000]			[0.000]		
Observations	19,106	19,106	19,106	20,452	20,452	20,452
R-squared	0.592	0.170	0.143	0.586	0.131	0.109
Country + industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
Establishment-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Workforce composition	Yes	Yes	Yes	Yes	Yes	Yes
Competitive/Uncertain environment	Yes	Yes	Yes	Yes	Yes	Yes
Manager's controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Table reports IV estimates: ER presence is instrumented using a dummy coded 1 if establishment-level wages are negotiated at a higher level (sectoral/national level) through collective bargaining agreements. In columns 2-3, the dependent variable is a dummy variable indicating whether the establishment uses robots, i.e. programmable machines that are capable of carrying out a complex series of actions automatically. In columns 5-6, the dependent variable is a dummy variable indicating whether the establishment uses data analytics to improve the processes of production or service delivery, where data analytics refers to the use of digital tools for analysing data collected at this establishment or from other sources. Establishment-level controls: plant size, plant age, multi-site. Workforce composition: % permanent contracts, % part-time workers. Competitive/uncertain environment: predictability of demand and competitive pressures as perceived by the manager. Manager's characteristics (gender, position). *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Use of robots and ER: mechanisms

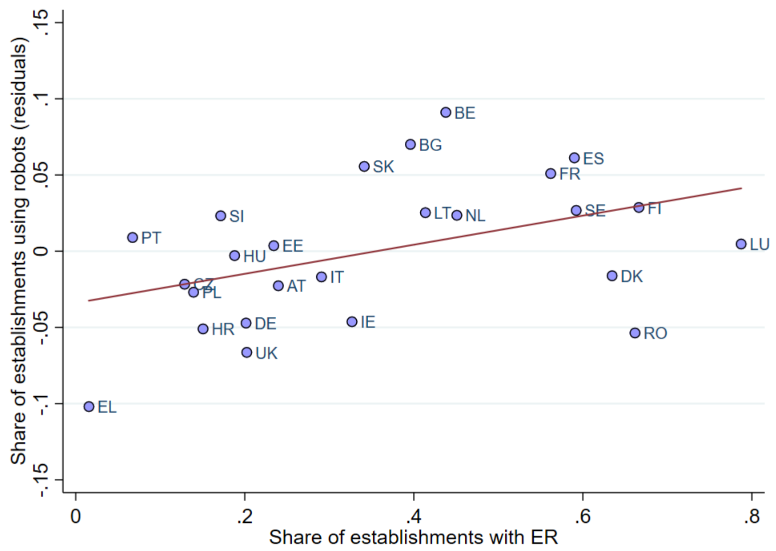
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ER	0.014**	0.012**	0.012*	0.009	0.005	0.003	0.014**
	(0.006)	(0.006)	(0.007)	(0.008)	(0.009)	(0.008)	(0.006)
Strike	0.023	0.027					
	(0.025)	(0.025)					
Bad work climate		-0.019***					
		(0.007)					
ER × Strike	-0.005	-0.008					
	(0.034)	(0.034)					
ER × Bad work climate		0.011					
		(0.013)					
Employee influence on layoffs			0.012*				
			(0.006)				
ER × Employee influence on layoffs			0.017				
			(0.013)				
Employee influence on training				0.014***			
				(0.005)			
ER × Employee influence on training				0.006			
				(0.010)			
Employee influence on organization					0.012**		
					(0.005)		
ER × Employee influence on organization					0.014		
					(0.010)		
Employee influence on working time						0.013***	
						(0.005)	
ER × Employee influence on time						0.018*	
						(0.010)	
Reduced employment							-0.020***
							(0.007)
ER × Reduced employment							0.006
							(0.013)
Observations	19,106	19,106	15,758	18,201	18,425	17,412	19,106
R-squared	0.170	0.170	0.173	0.170	0.171	0.174	0.170

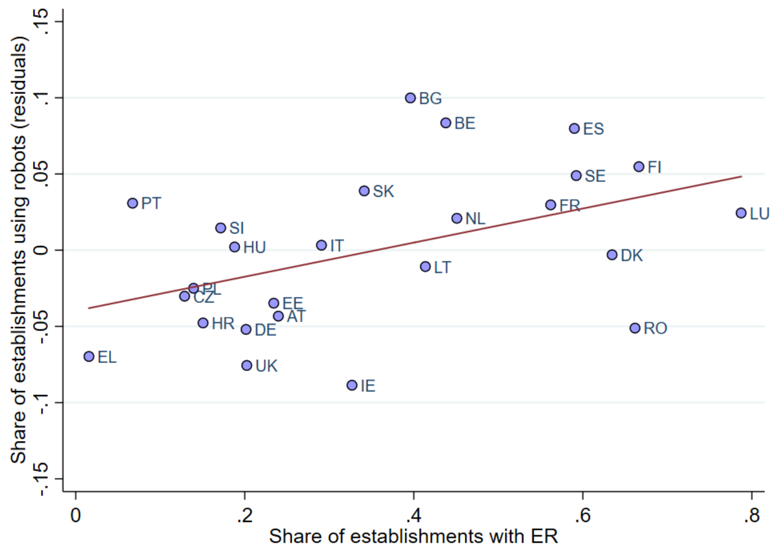
Notes: Estimates from LPM models with robust standard errors in parentheses. The dependent variable is a dummy variable indicating whether the establishment uses robots, i.e. programmable machines that are capable of carrying out a complex series of actions automatically. The variable strike takes value 1 if the establishment experienced an industrial action in the last three years (strikes, work-to-rule, or manifestations). The variable "Employee influence" takes value 1 if (according to the manager), employees exert moderate to great influence on layoffs, training, work organization or working time arrangements. *** p<0.01, ** p<0.05, * p<0.1.

APPENDIX

A.1 Additional Results: Figures and Tables

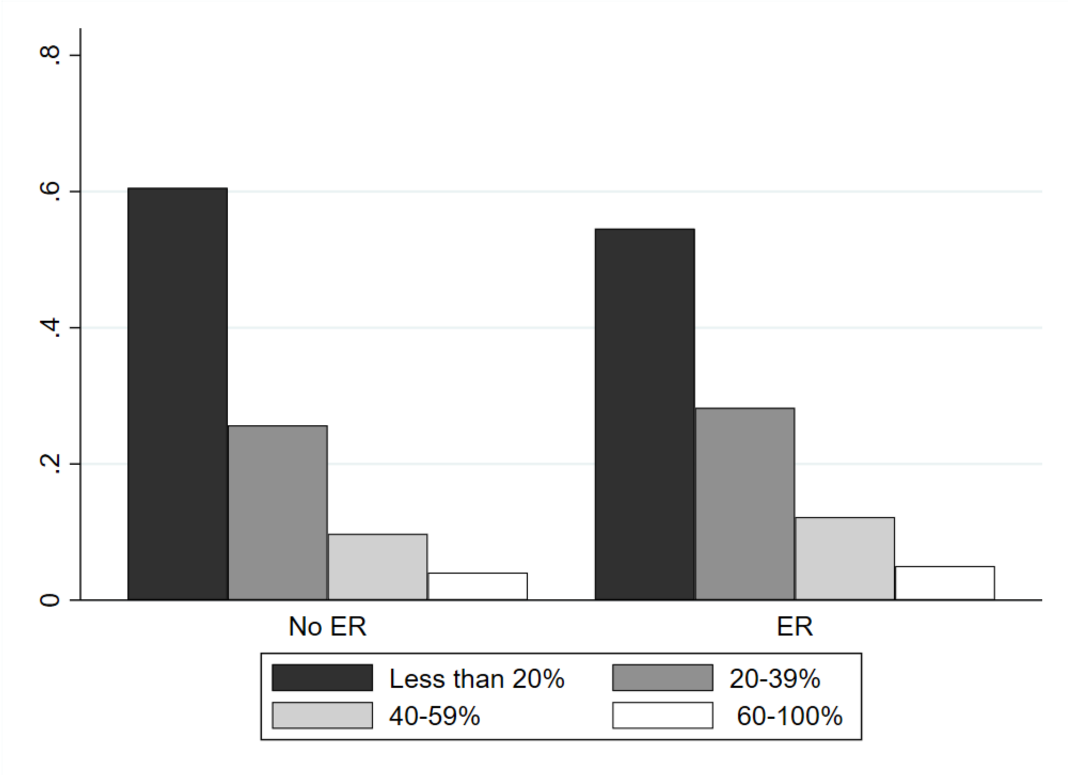
Figure A.1.1: Robot usage (residual) and ER. Manufacturing





Notes: Pooled data from the European Company Survey 2019. Observations from Malta, Cyprus and Latvia are excluded due to low number of cases. Sample weights are used. The figures display the cross-country correlation between the (residual) share of establishments using robots and the share of establishments with ER. Robot usage is purged from country differences in GDP and ageing. These values are obtained as residuals from regressing the share of establishments using robots against countries' GDP/1000 in PPP (the regression coefficient of GDP is 0.005, with p-value=0.000) and the change in the ratio of older workers (who are above the age of 54) to middle-aged workers (between the ages of 20 and 54) computed from UN Population Statistics (the regression coefficient of ageing is 0.358, with p-value=0.007). In the right panel, we use the change in the ratio of older workers to middle-aged workers between 1990 and 2015.

Figure A.1.2: Fraction of workers aged 50+ by workplace ER status (ECS 2013)



Notes: Pooled data from the European Company Survey 2013.

Table A.1.1: Use of robots and ER in rapidly-ageing and slowly-ageing countries.

VARIABLES	(1) All countries	(2) Rapidly-ageing countries	(3) Slowly-ageing countries
ER	0.015**	0.019**	0.009
	(0.007)	(0.008)	(0.007)
Share of workers aged 50+ >60%	-0.190***		
	(0.072)		
ER × Share of workers aged 50+ >60%	-0.010		
	(0.108)		
Observations	19,100	9,480	9,626
R-squared	0.170	0.164	0.179
Country + industry dummies	Yes	Yes	Yes
Establishment-level controls	Yes	Yes	Yes
Workforce composition	Yes	Yes	Yes
Competitive/Uncertain environment	Yes	Yes	Yes
Manager's controls	Yes	Yes	Yes

Notes: Estimates obtained from LPM models with robust standard errors in parentheses. In columns 1-3, the dependent variable is a dummy variable indicating whether the establishment uses robots, i.e. programmable machines that are capable of carrying out a complex series of actions automatically. Estimates reported in column (1) control for a dummy variable equal to 1 if the fraction of employees aged 50+ is greater than 60% (information merged at the size-industry-country cell using ECS 2013). In columns (1)-(2), sample split based on whether the establishment is located in rapidly-ageing (above median) or slowly-ageing country (below median). The indicator of ageing is the 1950-1990 change in the ratio of older workers (who are above the age of 54) to middle-aged workers (between the ages of 20 and 54) computed from UN Population Statistics. Establishment-level controls: plant size, plant age, multi-site. Workforce composition: % permanent contracts, % part-time workers. Competitive/uncertain environment: predictability of demand and competitive pressures as perceived by the manager. Manager's characteristics (gender, position). *** p<0.01, ** p<0.05, * p<0.1.

Table A.1.2: Presence of ER and intensity of employee voice across different managerial domains.

VARIABLES	(1) Layoffs	(2) Training	(3) Organization	(4) WorkingTime
ER	-0.003	0.030***	-0.007	0.030***
	(0.008)	(0.009)	(0.008)	(0.009)
Observations	16,992	19,541	19,794	18,728
R-squared	0.035	0.052	0.042	0.064
Country + industry dummies	Yes	Yes	Yes	Yes
Establishment-level controls	Yes	Yes	Yes	Yes
Workforce composition	Yes	Yes	Yes	Yes
Competitive/Uncertain environment	Yes	Yes	Yes	Yes
Manager's controls	Yes	Yes	Yes	Yes

Notes: Columns 1-4 report estimates from LPM models with robust standard errors in parentheses. The dependent variable (Influence) takes value 1 if (according to the manager), employees exert moderate to great influence on layoffs, training, work organization or working time arrangements. Establishment-level controls: plant size, plant age, multi-site. Workforce composition: % permanent contracts, % part-time workers. Competitive/uncertain environment: predictability of demand and competitive pressures as perceived by the manager. Manager's characteristics (gender, position). *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.1.3: Intensity of ER influence and use of robots (only establishments with ER)

	(1)	(2)	(3)	(4)	(5)
ER influence on layoffs	0.013				0.003
	(0.012)				(0.013)
ER influence on training		0.019**			0.021*
		(0.009)			(0.013)
ER influence on organization			0.007		-0.012
			(0.009)		(0.013)
ER influence on working time				0.030***	0.029**
				(0.009)	(0.013)
Observations	5,428	6,429	6,471	6,102	5,123
R-squared	0.211	0.214	0.213	0.221	0.220
Country + industry dummies	Yes	Yes	Yes	Yes	Yes
Establishment-level controls	Yes	Yes	Yes	Yes	Yes
Workforce composition	Yes	Yes	Yes	Yes	Yes
Competitive/Uncertain environment	Yes	Yes	Yes	Yes	Yes
Manager's controls	Yes	Yes	Yes	Yes	Yes

Notes: Estimates restricted to establishments with ER. Columns 1-4 report estimates from LPM models with robust standard errors in parentheses. The dependent variable (Influence) takes value 1 if (according to the manager) ER bodies exert moderate to great influence on dismissals, training, work organization or working time arrangements. Establishment-level controls: plant size, plant age, multi-site. Workforce composition: % permanent contracts, % part-time workers. Competitive/uncertain environment: predictability of demand and competitive pressures as perceived by the manager. Manager's characteristics (gender, position). *** p<0.01, ** p<0.05, * p<0.1.

Table A.1.4: Use of robots and ER in countries with high/low employment protection.

Variables	(1) Use of robots (Low EPL)	(2) Use of robots (High EPL)
ER	0.021**	0.008
	(0.008)	(0.007)
Observations	8,250	10,856
R-squared	0.186	0.158
Country + industry dummies	Yes	Yes
Establishment-level controls	Yes	Yes
Workforce composition	Yes	Yes
Competitive/Uncertain environment	Yes	Yes
Manager's controls	Yes	Yes

Notes: Estimates obtained from LPM models with robust standard errors in parentheses. The dependent variable is a dummy variable indicating whether the establishment uses robots, i.e. programmable machines that are capable of carrying out a complex series of actions automatically. Sample split based on whether the establishment is located in a country where the 2019 OECD EPL indicator of strictness of employment protection on individual and collective dismissals (regular contracts) is below (low EPL) or above (high EPL) the median value in OECD countries. Establishment-level controls: plant size, plant age, multi-site. Workforce composition: % permanent contracts, % part-time workers. Competitive/uncertain environment: predictability of demand and competitive pressures as perceived by the manager. Manager's characteristics (gender, position). *** p<0.01, ** p<0.05, * p<0.1.

Table A.1.5: Use of robots and ER: sample split based on degree of centralization (high/low) of the wage-setting process

Variables	(1) Use of robots (Low wage centralization)	(2) Use of robots (High wage centralization)
ER	0.002	0.021***
	(0.008)	(0.008)
Observations	9,557	9,549
R-squared	0.131	0.206
Country + industry dummies	Yes	Yes
Establishment-level controls	Yes	Yes
Workforce composition	Yes	Yes
Competitive/Uncertain environment	Yes	Yes
Manager's controls	Yes	Yes

Notes: Estimates obtained from LPM models with robust standard errors in parentheses. The dependent variable is a dummy variable indicating whether the establishment uses robots, i.e. programmable machines that are capable of carrying out a complex series of actions automatically. The degree of centralization of wage setting systems measured as the average incidence of higher-level wage bargaining (industry, region or national level) in each industry-country cell. Sample split based on whether the establishment is located in a industry-country cell below or above the median value of wage centralization. Establishment-level controls: plant size, plant age, multi-site. Workforce composition: % permanent contracts, % part-time workers. Competitive/uncertain environment: predictability of demand and competitive pressures as perceived by the manager. Manager's characteristics (gender, position). *** p<0.01, ** p<0.05, * p<0.1.