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Advanced Technologies and Worker Voice

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The interplay between labour institutions and firm-level adoption of new technologies such as robotics and other advanced digital tools remains poorly understood. Using a cross-sectional sample of more than 20,000 European establishments, we document a positive association between shop-floor employee representation (ER) and utilization of emerging technologies. We explore mechanisms driving this correlation by exploiting rich information on the role played by ER in relation to well-defined decision areas of management, such as work organization, dismissals, training and working time. In addition, we conduct a quantitative case study using a panel of Italian firms and exploiting size-contingent policy rules governing the operation of ER bodies in the context of a local-randomization regression discontinuity design. The analysis suggests a positive effect of ER on investments in advanced technologies around the firm size cut-off, although results are sensitive to type of technology and specification choices. We also document positive effects on training and process innovation, and no evidence of changes in composition of employment. Our findings cast doubt on the idea that ER discourages technology adoption. Rather, ER seems to influence workplace practices that enhance the complementarity between labour and new advanced technologies.

INTRODUCTION

The use of advanced technologies in the workplace has improved significantly in recent years (Haenlein and Kaplan 2019), finding wide applications in many industries (e.g. Graetz and Michaels 2018; Acemoglu and Restrepo 2020). Such trends have been investigated extensively in the literature, especially with reference to their potential implications for labour displacement (Brynjolfsson and McAfee 2014; Goos 2014; Autor 2015; Ford 2015; Susskind and Susskind 2015; Aghion *et al.* 2021). Much less attention has been paid to the factors that drive the adoption of advanced technologies in the first place. In particular, little is known about the role played by labour market institutions in relation to these technologies.

In this paper, we study whether the firm-level adoption of advanced technologies such as robots and other advanced digital tools is influenced by the presence of shop-floor employee representation (ER), that is, the typical establishment-level institution for employee voice (e.g. unions, works councils) through which workers exert an influence on work organization and employment-related issues, as exists in many European countries. Industrial robots and advanced digital tools are two broad sets of tangible (the former) and intangible (the latter) automated capital available to firms. Robots are programmable machines capable of carrying out complex series of actions automatically. Advanced digital tools refers to a broad set of new technologies for analysing data through the production process on the basis of automated information gathering and analysis (e.g. big data analytics, the internet of things, virtual reality, cybersecurity).

From a theoretical point of view, the effect of ER on the use of these technologies is ambiguous. A commonly held perspective is that ER negatively affects investments in robots and digitalization via hold-up (Grout 1984). Moreover, ER may discourage technology adoption by delaying management decisions through the imposition of time-consuming consultations (Genz *et al.* 2019). According to this view, granting workers control rights raises their bargaining power and thereby discourages investments in advanced technologies. At the same time, however, ER can affect technology adoption through a number of alternative channels leading to opposite predictions. For instance, in the standard competitive model, ER can rise wages above the market level, inducing (under certain conditions) the replacement of labour with automated capital. The same effect may show up if the presence of ER is aimed at protecting insiders through rigid and conflicting employment relationships (Fornino and Manera 2022; Presidente 2020). Alternatively, ER may enable the adoption of advanced technologies through its effect on information flows, labour–management cooperation and work organization (Freeman and Lazear 1995). In particular, the more ER favours work systems that allow for information-sharing and retraining, as well as the targeting of unhealthy and unpleasant task replacement, the more ER will be positively associated with deeper use of complementary advanced technologies. The aim of this paper is to provide evidence that helps to disentangle these different channels.

Our empirical analysis proceeds in two steps. First, we explore the correlation between ER and the utilization of advanced technologies by using granular information from unique establishment-level data collected as part of the last wave of the European Company Survey (from 2019). Such correlational analysis allows us to obtain preliminary descriptive evidence about this relationship that spans a large number of European countries. Moreover, this survey contains rich information about ER activity within establishments, which allows many of the channels outlined above to be investigated. Then, in the second part of the paper, we study the causal nature of the association between ER and advanced technologies adoption through a case study based on a regression discontinuity design (RDD). In particular, our identification approach rests on size-contingent labour market regulations in Italy, and exploits the fact that Italian workers have the right to establish ER bodies (if requested) in firms employing more than 15 employees. Focusing on a single country allows us to take into better account specific nuances of the national legislation and rely on firm-level longitudinal information. In this way, we hold constant potential confounders that compromise identification in our descriptive analysis based on cross-country establishment-level data. Since our running variable is discrete and contains mass points, we rely on the new local randomization RDD approach developed by Cattaneo *et al.* (2015, 2016).[1]

We obtain the following results. At the descriptive level, we find no evidence of a negative association between ER and the use of advanced technologies. Rather, in all cross-country specifications, we obtain a positive and statistically significant effect. This holds for both robots and advanced digital tools, and regardless of the extent of ER involvement in dismissal decisions at workplace level. In addition, ER is more strongly correlated with the adoption of these technologies in countries characterized by relatively low employment protection. Moreover, the positive association between ER and the use of such advanced technologies does not seem to result from employers' strategic bargaining responses induced by more adversarial employment relationships, as measured by past strike activity. Overall, these results cast doubts on the idea that ER may spur automation by reducing the flexibility of employment relationships. On the contrary, the effect of ER on advanced technologies is picked up when we control for measures of the intensity of ER influence on training, work organization, working-time management, and the use of information-sharing mechanisms, pointing to the design of communication and work systems as a potentially relevant mechanism. Additional descriptive estimates show that ER fosters the use of robots mainly in establishments located in rapidly ageing countries, that is, precisely in environments where the relative scarcity of middle-aged workers would dictate so (Acemoglu and Restrepo 2021). Moreover, the correlation between ER and robots is driven by workplaces operating in industry–country cells with a higher fraction of workers performing unpleasant and physically demanding tasks. Interestingly, the positive effect of ER on both robots and advanced digital tools is stronger in workplaces operating in highly centralized wage-setting environments, where one would expect a more limited influence of shop-floor ER on wages.

When we zoom in our focus on Italy and look at the causal effect of ER bodies on investments in advanced technologies for firms around the size cut-off, we obtain broadly consistent results. The impact of ER, however, varies depending on specification choices and the type of technology. In our preferred specification, using a local-constant polynomial approximation, the effect of ER bodies on robot acquisitions is statistically insignificant. In turn, greater employee voice channelled through ER bodies raises the acquisition of advanced digital tools by 6 percentage points. This effect is equivalent to 12% of standard deviation of the outcome variable in the control group. We also document a positive effect of ER on investments in conventional information and communication technologies (ICT). Overall, our RDD estimates provide no evidence that ER discourages technology adoption. The fact that ER has apparently no effect on robot acquisitions, while simultaneously favouring investments in advanced digital tools and ICT, suggests that worker voice fosters the complementarity between labour and certain types of advanced technology.

When we dig into the mechanisms, we find that ER is associated with discontinuities neither in employment outcomes (employment growth, hires, separations, vacancies) nor in workforce composition (share of production workers, education levels, age groups, employment contracts). At the same time, treated firms report greater incidence of both training activities and process innovation. As part of our RDD, we account for other confounding regulations affecting firms around the cut-off, and perform a battery of validation and robustness checks. Altogether, our findings suggest that, if anything, the positive association between ER and advanced technologies is more likely to be driven by complementary organizational changes favoured by ER than by pure capital–labour substitution mechanisms.

Our paper is most closely related to the theoretical and empirical literature on the relationship between technology and labour. Rather than focusing on the labour market effects of advanced technologies, we study whether labour market institutions aimed at fostering worker voice shape their adoption in the first place.[2] While some recent studies have begun to address similar issues, they rely on *de jure* measures of labour rights and ER, and take an aggregate (country- or industry-level) perspective, without digging into cross-firm heterogeneity (e.g. Presidente 2020). An emerging literature focuses on the firm-level determinants of automation (Cheng *et al.* 2019; Koch *et al.* 2021; Zolas *et al.* 2020; Fan *et al.* 2021; Deng *et al.* 2021). In particular, few recent papers address the role of ER in relation to the adoption and consequences of advanced technologies from a micro-level perspective.[3] Dauth *et al.* (2021) find smaller displacement effects of robot adoption in highly unionized environments in Germany due to reshuffling of tasks and retraining of workers within firms. Battisti *et al.* (2021) show that unions contribute to smooth the transition of workers from routine to abstract tasks within German firms in response to technological changes, by facilitating retraining and skill upgrading. Genz *et al.* (2019) show that the existence of works councils reduces the use of digital technologies in German plants, although the effect is reversed in establishments employing a high share of workers performing physically demanding jobs.

We add to this small but growing literature in three distinct ways. First, we provide direct micro-level evidence on the relationship between worker voice and adoption of advanced technologies, using both a large cross-sectional sample of European workplaces and a panel of Italian firms, and accounting for a wide range of technologies (robotics, advanced digital tools and more conventional ICT). Second, we open the black box of ER activity within firms by exploiting rich information on the *de facto* influence exerted by employee representatives in relation to well-defined decision areas of management, such as dismissals, training, work organization and time management. We provide evidence consistent with the idea that worker voice is not an obstacle to advanced technologies adoption. Rather, it favours certain workplace practices associated with high-performance work systems, such as training and information-sharing, that may be complementary to these technologies (Kochan *et al.* 2020).[4] Finally, we complement our correlation analysis with a causal research design in the context of a country-specific study by leveraging policy-induced quasi-experimental variation in the probability of ER presence across firms.

Our work also 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 recognize that granting workers control rights can have deleterious effects on firm investments (Jensen and Meckling 1979; Lindbeck and Snower 1989). While the focus of most analyses is 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). Overall, the evidence stemming from this literature 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; Berton *et al.* 2022). More directly related to our work, Addison *et al.* (2007) explicitly take into 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. More recently, Jäger *et al.* (2014) provide causal evidence that worker participation in firm governance via co-determination rights (board-level ER) has no effects on wages and raises physical capital formation. We add to this literature by studying whether shop-floor ER affects the utilization of modern technologies such as robots and other advanced digital tools. Although these technologies are likely to become production assets of growing importance in years to come, the understanding of the institutional forces driving their adoption and mediating their consequences is still insufficient. In this paper, we take some steps towards filling this gap.

The remainder of the paper is organized as follows. Section I discusses the theoretical channels through which ER may affect the use of advanced technologies. Section II reports the results of the correlational analysis at the European level, which includes the exploration of possible alternative mechanisms driving the relationship between ER and advanced technologies. Section III investigates the causal effect of ER on technology adoption through an RDD design based on Italian data. Section IV concludes.

I. Theoretical Mechanisms

Rent-seeking, hold-up and delayed decisions

Conventional views in the economics literature suggest that unions and other forms of ER exert a negative impact on capital formation and technology adoption. In the absence of binding employment contracts, institutions that give control rights to workers strengthen their capacity to *extract rents* (Grout 1984). Anticipating this, employers may reduce investments in technology to avoid a relative large share of quasi-rents stemming from such investments being *ex post* appropriated by labour. Following this line of reasoning, higher incidence of shop-floor ER bodies should be associated with lower investment in capital goods, including those related to automation.

Moreover, the presence of ER bodies at workplace level may increase the costs of technological restructuring in other ways. As argued by Genz *et al.* (2019), in fact, ER allows employees to exert greater control rights over a wide range of organizational changes taking place in the workplace, including the introduction of new technologies. In most contexts, employee representatives have the right to be informed and consulted on issues related to job displacements, work safety and employee monitoring affecting the existing workforce. Since technologies such as robots and other advanced digital tools have the potential to affect all these dimensions, ER gains substantial scope of action regarding the process that leads to their actual adoption, while limiting the freedom of action of the management. Hence the implementation of these technologies might consume considerably longer time in the presence of ER compared to the cases where ER is absent. Delay costs associated with the presence of ER bodies may impede firms to respond to profitable market opportunities in a timely manner, discouraging the use of technologies in the first place (Freeman and Lazear 1995).

Monopoly power, labour conflict and insider protection

Opposite predictions, however, can be obtained by considering a set of institutional frictions commonly associated with the presence of ER. The most direct one is related to the fact that ER institutions can push wages above the competitive level. In the standard competitive model, the impact of a wage increase on the demand for labour and capital can be divided into two effects. First, there is a substitution effect as higher wages reduce the relative price of capital and provide incentives to replace labour by machines. Second, there is a scale effect as less output is produced after the wage increase. If the substitution effect dominates the scale effect, then ER may induce firms to adopt automated capital at a faster rate as a way to substitute away costly labour (Denny and Nickell 1991; Booth 1995).[5] The presence of ER bodies may also induce more automation by reducing the flexibility of labour contracts. In this respect, Fornino and Manera (2022) suggest that flexibility represents the distinctive comparative advantage of labour, which makes it better suited than automated capital to cope with idiosyncratic shocks faced by firms. It follows that if strong ER bodies oppose flexible employment in order to protect insiders (see, for example, Heery 2004; Salvatori 2012; Visser 2002), then such an advantage would disappear, allowing factor substitution to proceed faster. As a result, we should expect the presence of ER to be associated with positive investments in robots and advanced digital tools, and higher job displacement rates, especially in contexts where ER bodies exert an influence on dismissals procedures and operate under stringent employment protection legislation.[6]

Finally, in the presence of conflicting interests between employers and workers, technological choices may also be driven by strategic considerations regarding work discipline at the firm level. The adoption of new technologies may indeed be part of employers' strategic response aimed at disorganizing labour and eroding workers' bargaining power (Gintis 1976; Marglin 1974; Bowles 1985; Skillman 1988; Duda and Fehr 1987; Pagano 1991).[7] In our context, this approach would suggest that whenever ER bodies are combined with highly adversarial industrial relations, the use of robots and other advanced digital tools will rise. Recently, Presidente (2020) documents a positive association between lagged measures of strike activity and robot adoption at the industry–country level. He argues that labour-friendly institutions induce investment in industrial robots, particularly in sunk-cost intensive industries, where higher vulnerability to hold-up strengthen workers' bargaining power.[8]

Taken together, this strand of the literature predicts that as long as advanced technologies and human labour are sufficiently close substitutes, the presence of ER would create frictions (i.e. higher wages, less flexible employment contracts, more adversarial labour–management relations) that raise the relative cost of labour, inducing employers to replace workers with automated capital.

Complementarity between technology and work organization

Finally, ER may have a positive effect on technology adoption via its direct effect on work organization. This is especially relevant in the presence of organizational complementarities, that is, situations in which distinct workplace practices exert an influence on the profitability of others, which may explain potential clusters of practices and technological choices (Brynjolfsson and Milgrom 2012). In this framework, ER can favour work systems that are complementary to advanced technologies in three main respects. First, ER favours the internal transmission of information in a way that complements information processing based on new digital technologies, with potentially positive effects on the reorganization of production processes.[9] At the same time, works in industrial relations document that the presence of ER bodies may facilitate the internal flow of information to top decision-makers (Kaufman and Levine 2000; Belloc *et al.* 2020). Improved information transmission, search and processing may thus complement each other, generating larger incentives to invest in robots and advanced digital tools in establishments where ER is present. In the absence of ER, frontline workers may not disclose local knowledge that may be critical for the adoption of advanced technologies for fear that the firm will use that information against them (e.g. job cuts). In a context of technological restructuring, employee voice may reduce information asymmetries and facilitate the enforcement of implicit employment agreements between the firm and its workforce (Malcomson 1983; Hogan 2001). Second, several contributions document that unionization is often associated with higher investment in training, which may facilitate the acquisition of new skills that are complementary to advanced technologies (Dustmann and Schönberg 2009; Martins 2019). Third, workplace governance systems based on ER can be complementary to rich job designs, reducing workers' exposure to job automation risk and enabling greater labour–technology complementarity (Belloc *et al.* 2022). This may in turn favour the selection of efficiency-enhancing technologies, which at the same time improve working conditions.[10] Moreover, it may reduce workers' hostility towards technology adoption, allowing for processes of job redesign and retraining to take place. In this context, the adoption of advanced technologies may not necessarily be accompanied by employment losses for workers. Taken together, these different mechanisms suggest that, in the presence of ER, high adoption rates of new technologies can go together with relatively cooperative industrial relations that promote processes of organizational restructuring.

Summary

We identify three main mechanisms thorough which ER can affect investments in advanced technologies: hold-up/delayed decisions, institutional frictions, and technology–organization complementarity. While the first of these predicts a negative association between ER and technology adoption, the remaining two suggest adoption to correlate positively with ER. Depending on the mechanism, however, such correlation should be conditional on the actual role played by ER bodies (e.g. training, information-sharing) and other features of the employment relationship such as the stringency of employment protection, task composition and industrial relations climate. Moreover, even if there are competing channels explaining a positive relationship between ER and advanced technologies, they lead to different predictions in relation to the employment consequences of technological change for workers. Variation across these dimensions will be exploited in the empirical analysis to discriminate among mechanisms.

II. Evidence from EU Workplaces

The European Company Survey

In the first step of our empirical analysis, we explore the relationship between ER and technology adoption by using establishment-level data from the European Company Survey (ECS) 2019 (van Houten and Russo 2020). ECS data cover a representative sample of non-agricultural establishments employing at least ten employees and located in all EU countries.[11] A crucial advantage of this survey is that it provides harmonized cross-country information on ER and use of advanced technologies. In addition, the survey reports rich details about management practices and organizational design at workplace level.

Measure of shop-floor ER We focus on institutionalized forms of ER. Employee representation is a dummy variable identifying establishments with a trade union, works council or any other country-specific official structure of ER (e.g. joint consultative committees).

Measure of robots and advanced digital tools The survey provides information on establishment-level utilization of advanced technologies. Our first 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 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 10,000 employees) as reported by the International Federation of Robotics (IFR). Both measures are positively correlated. This is reassuring, considering that IFR data on robot

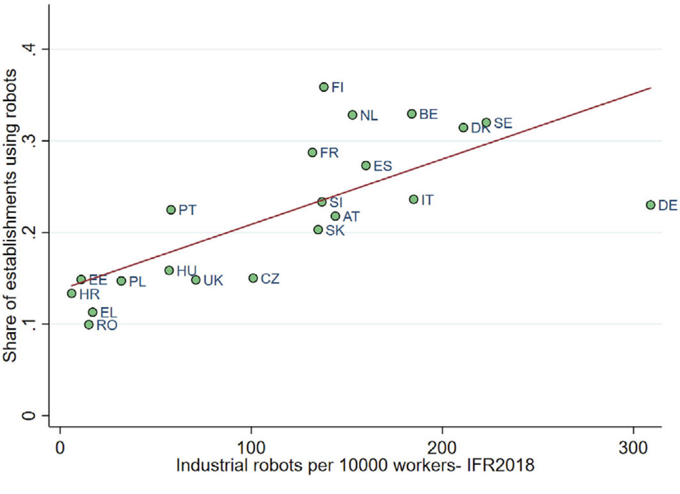

FIGURE 1. Robot usage and robot density in Manufacturing. *Notes*: Pooled data from the European Company Survey 2019. Robot usage refers to establishments using 'programmable machines that are capable of carrying out a complex series of actions automatically'. Robot density is the number of industrial robots per 10,000 workers (Source: International Federation of Robotics, 2018).

density have been used extensively in the literature. In addition, we analyse the association between the presence of ER and the utilization of advanced digital tools such as data analytics, that is, a dummy variable equal to 1 if the establishment uses 'data analytics to improve the process of production and service delivery'. Unfortunately, the question is framed in a very general way as it refers to data analytics as 'digital tools for analysing data collected at this establishment or from other sources'. Although the reference to data analysis based on multiple information sources hints at technologies that are somewhat more advanced than conventional ICT, we cannot exclude that respondents conceived data analytics as a relatively broad set of technologies. For this reason, we consider such a variable as a general index of advanced digitalization at the establishment.

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 and permanent employees), and changes in employment in the last three years. Moreover, managers provide detailed information on the extent to which ER bodies 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, perceived work climate and practices related to information dissemination. This rich set of information allows us to test for specific mechanisms and control for well-known establishment-level drivers of technology adoption.

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. As expected, the share of workplaces using robots is higher in Manufacturing (22%).[12] The use of other advanced digital tools is more widespread, being present in 45% of the establishments. Both technologies are more common among establishments with ER. Figure 2 shows the share of establishments using robots and other advanced digital tools by country and workplace ER status. Figures 3 and 4 document the adoption of such advanced technologies across establishments with different characteristics. The larger average use of robots and advanced digital tools under ER seen in the previous figures seems robust across establishments with different age, different size, different use of permanent and part-time contracts, and facing different levels of market competition and demand predictability. Interestingly, Figure 5 shows that the utilization of robots and advanced digital tools is higher in establishments with ER regardless of past and projected changes in the level of employment. In other words, the more intense use of advanced technologies under worker voice arrangements holds for both growing and shrinking establishments.

Correlation between ER and the use of advanced technologies

We begin by considering the baseline regression model

$$Y_{ijc} = \beta_0 + \beta_1 \, \mathrm{ER}_{ijc} + \mathbf{bX}_{ijc} + \varepsilon_{ijc}, \tag{1}$$

where subscripts i, j and c denote the establishment, industry and country, respectively; Y_{ijc} is a dummy variable equal to 1 if establishment i in industry j located in country c uses advanced technologies, either robots or other advanced digital tools; ER_{ijc} is a dummy variable for the presence of ER at the establishment level; $\mathbf{X}_{ijc}$ is the vector of controls; and 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.

TABLE 1
MAIN VARIABLES: DESCRIPTION AND DESCRIPTIVE STATISTICS

Variables	Description as in the ECS questionnaire	Mean	S.D.
ER	An official ER currently exists in the establishment (yes/no)	0.247	0.432
Robots	Machines carrying out complex actions automatically are used (yes/no)	0.073	0.261
Advanced digital tools	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	35.241	35.086
Multi-site	This is one of more establishments belonging to the same company (yes/no)	0.244	0.429
Change in ownership	There has been any change in the ownership of the company in the last three years (yes/no)	0.184	0.387
Permanent workers < 20%	Employees in the establishment with an open-ended contract are < 20% (yes/no)	0.082	0.274
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	0.427
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)	0.261	0.439
Part-time workers > 80%	Employees in the establishment working part-time are > 80% (yes/no)	0.054	0.225
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)	0.499	0.500
Market competition: low	The market for the main product/service is not very competitive (yes/no)	0.105	0.306
Market competition: null	The market for the main product/service is not competitive at all (yes/no)	0.030	0.171
Market uncertainty: high	The market for the main product/service is not predictable at all (yes/no)	0.077	0.267
Market uncertainty: med	The demand for the main product/service is not very predictable (yes/no)	0.572	0.495
Market uncertainty: low	The demand for the main product/service is fairly predictable (yes/no)	0.288	0.453
Market uncertainty: null	The demand for the main product/service is very predictable (yes/no)	0.042	0.200
Manager gender	The manager answering to the questionnaire is a woman	0.519	0.500
Manager position: general	Position held by the manager: general manager (yes/no)	0.184	0.387
Manager position: owner	Position held by the manager: owner-manager (yes/no)	0.205	0.404
Manager position: HR	Position held by the manager: human-resources 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)	0.170	0.376
Manager position: other	Position held by the manager: other (yes/no)	0.245	0.430

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

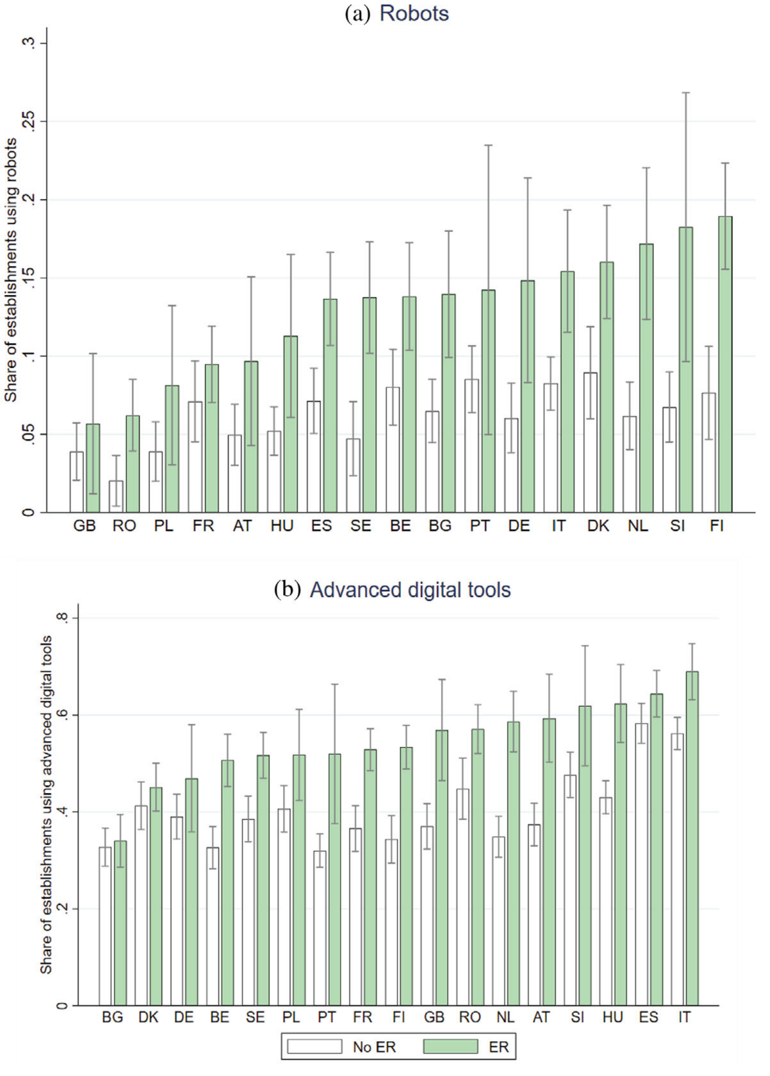

FIGURE 2. Robot and other advanced digital tools usage by workplace ER status in selected countries. *Notes*: Pooled data from the European Company Survey 2019 (selected countries). Sample weights are used. The use of robots refers to establishments using 'programmable machines that are capable of carrying out a complex series of actions automatically'. Advanced digital tools refers to establishments using 'digital tools for analysing data collected at this establishment or from other source' to improve the processes of production or service delivery.

In columns (1)–(5) of Table 2, we report the results from estimating a series of linear probability models where the dependent variable is the use of robots. In column (1), we estimate a model in which we include only a dummy variable that takes value 1 for establishments in which there is an ER body in place, and a full set of industry and country dummies.[13] The presence of ER is positively associated with the probability of using robots. In columns (2)–(5), we add more controls sequentially 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, its size as measured by the log of the number of employees, and a dummy variable taking value 1 for establishments subject

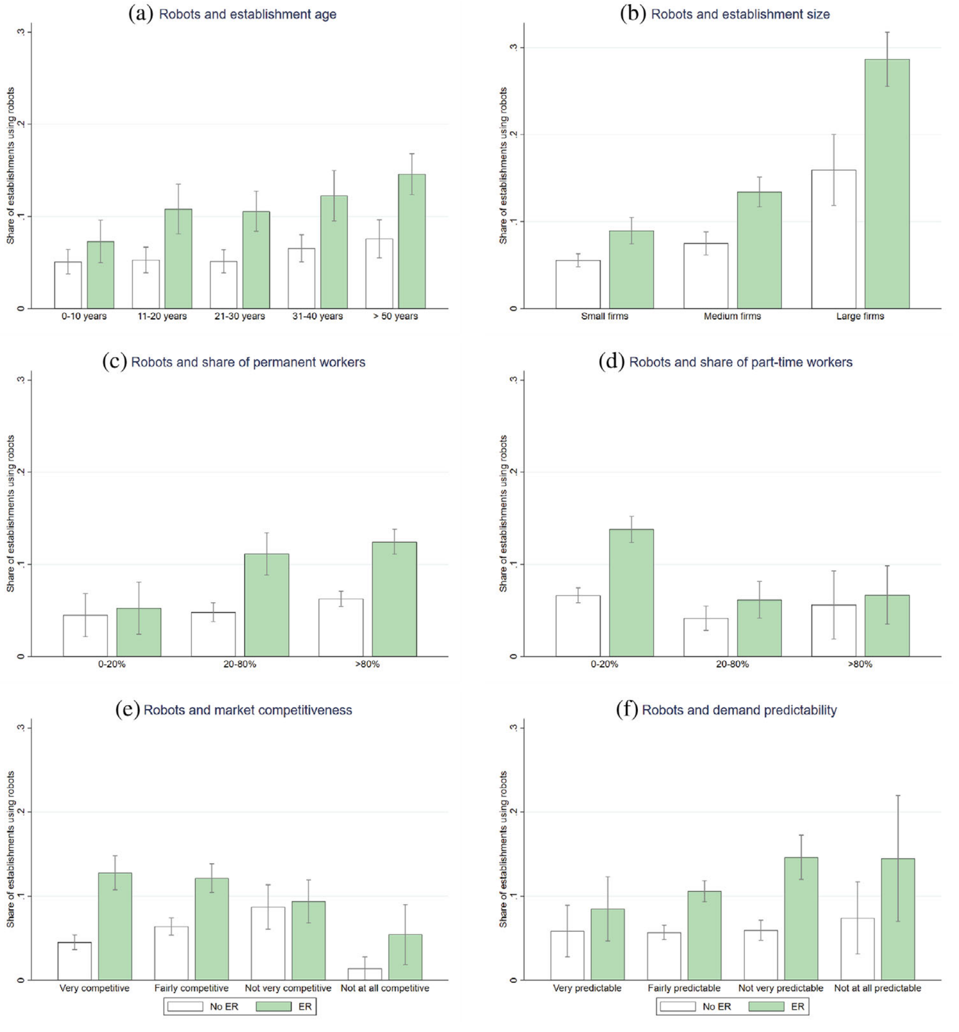

FIGURE 3. Robots and establishment characteristics. *Notes*: Pooled data from the European Company Survey 2019. Sample weights are used. Robots refer to establishments using 'programmable machines that are capable of carrying out a complex series of actions automatically'.

to a change in ownership during the last three years. 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 control additionally for proxies of the competitive environment faced by establishments, such as degree of market competition 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 a 1.4 percentage point increase in robot usage. Finally, in columns (6)–(10), we repeat the same exercise and add sequentially different groups of control variables in a model that has advanced digital tools as dependent variable. In our preferred specification, the presence of ER is associated with a 3.8 percentage point increase in the use of such advanced digital tools.[14]

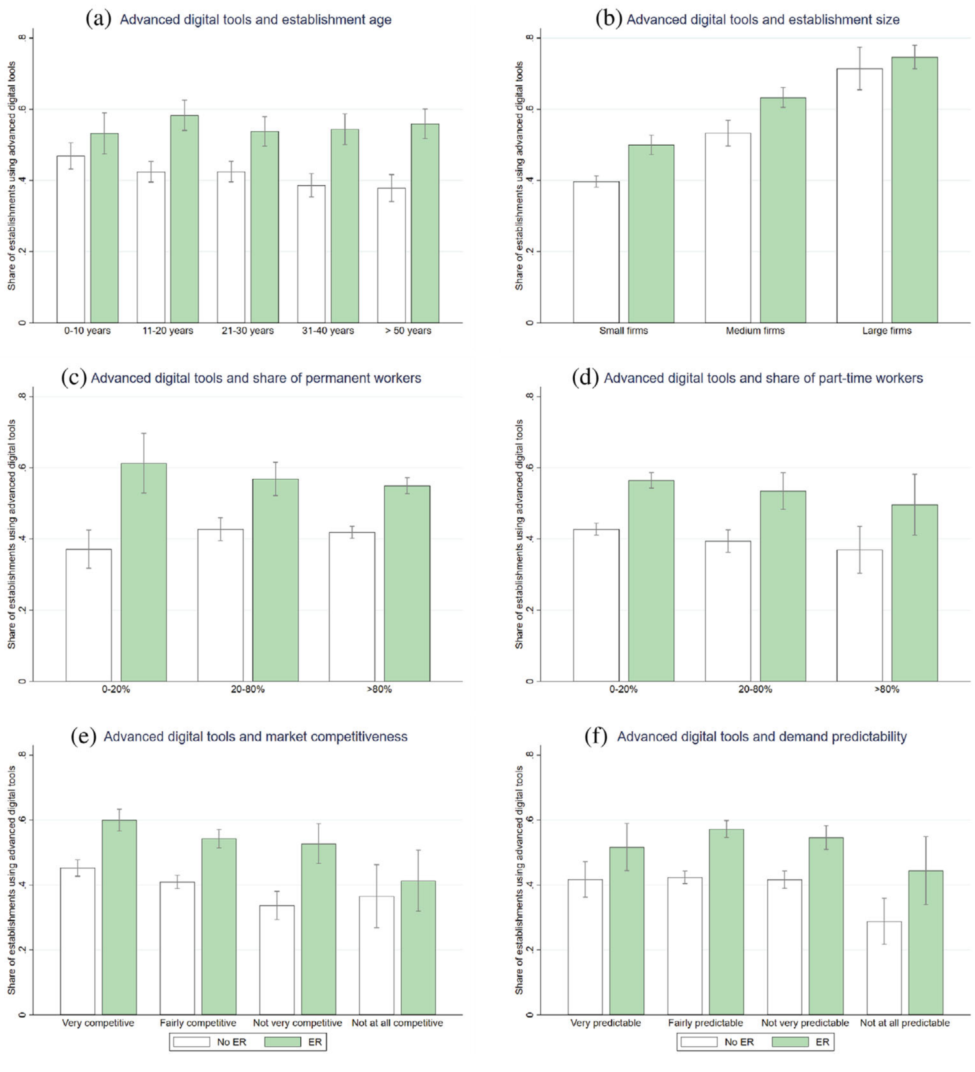

FIGURE 4. Advanced digital tools and establishment characteristics. *Notes*: Pooled data from the European Company Survey 2019. Sample weights are used. Advanced digital tools refer to establishments using 'digital tools for analysing data collected at this establishment or from other source' to improve the processes of production or service delivery.

In Table A.1.1 of the Online Appendix, we report additional estimates in which the ER dummy variable is unpacked into multiple categories; that is, unions, works councils and other types of ER are disentangled, and the absence of ER is the benchmark category. We find that works councils and trade unions are associated with a positive and statistically significant parameter in both models, while the coefficient of other types of ER turns out positive and significant only in relation to advanced digital tools.[15]

What drives the correlation between ER and the use of advanced technologies?

Having documented a positive correlation between ER and the use of both robots and advanced digital tools, we now turn to explore the plausibility of different channels discussed

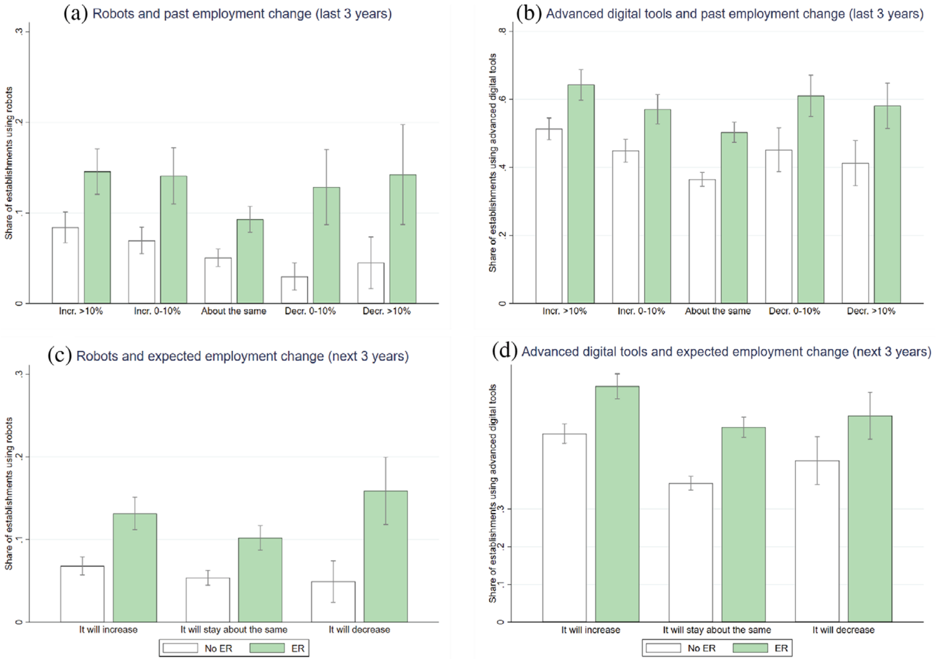

FIGURE 5. Robots and advanced digital tools by employment change status. *Notes*: Pooled data from the European Company Survey 2019. Sample weights are used. Robots refer to establishments using 'programmable machines that are capable of carrying out a complex series of actions automatically'. Advanced digital tools refer to establishments using 'digital tools for analysing data collected at this establishment or from other sources'.

in Section I. Thanks to the unique features of the data, we can open the black box of ER effects on technology adoption by looking at the intensive margin of ER influence with respect to different areas of workplace management.

Hold-up The standard hold-up framework posits that unionized firms may reduce investments in advanced technologies to prevent *ex post* quasi-rent extraction by workers. The presence of ER bodies may also discourage the use of new technologies by imposing time-consuming negotiations. In both cases, one should expect a negative correlation between ER and technology adoption. However, our empirical results show a positive coefficient, which points to exclude the plausibility of these channels, at least in their standard version. In this respect, notice that an implicit assumption behind the hold-up mechanism is that automation-related investments can be assimilated to any other capital inputs and are thus vulnerable to similar hold-up problems. This, however, may not be the case. Yet if advanced technologies such as robots do not have firm-specific features and can operate by themselves, or at least by involving a much smaller number of employees, then the *ex post* rent extraction strategy of the workers would be less credible. As a result, the discouraging effect of ER with respect to technology adoption would be much weaker (if not absent).

Labour conflict and insider protection An alternative hypothesis that we consider is that ER exacerbates institutional frictions in the employment relationship, thereby inducing firms to adopt advanced (arguably labour-saving) technologies. We test the plausibility of this channel by means of a set of different regressions.

First, we look at whether the presence of ER induces firm owners to introduce robots and other advanced digital tools in response to more adversarial labour–management relations.

TABLE 2
ROBOTS, ADVANCED DIGITAL TOOLS AND ER

	Robots					Advanced digital tools				
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ER	0.070***	0.016***	0.014***	0.015***	0.014**	0.150***	0.042***	0.041***	0.043***	0.038***
	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Observations	20,052	19,797	19,369	18,958	18,888	21,443	21,180	20,716	20,286	20,216
R-squared	0.138	0.168	0.171	0.170	0.171	0.078	0.123	0.124	0.129	0.134
Country + industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Establishment-level controls	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Workforce composition	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes
Competitive/uncertain environment	No	No	No	Yes	Yes	No	No	No	Yes	Yes
Manager's controls	No	No	No	No	Yes	No	No	No	No	Yes

Notes
Estimates obtained from linear probability 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 columns (6)–(10), the dependent variable is a dummy variable indicating whether the establishment uses digital tools for analysing data collected at this establishment or from other sources to improve the processes of production or service delivery. Establishment-level controls: plant size, plant age, multi-site, change in ownership. Workforce composition: % permanent contracts, % part-time workers. Competitive/uncertain environment: predictability of demand and competitive pressures as perceived by the manager. Manager's controls: gender and position.
***, **, * indicate $p < 0.01$, $p < 0.05$, $p < 0.1$, respectively.

To check for this, we estimate equation (1) while controlling for the occurrence of industrial actions in the last three years (strikes, works-to-rule or manifestations). Strike threats are an important tool to achieve higher wages and protect insiders (Booth 1995).[16] We also interact these variables with the dummy variable indicating the presence of ER. If technology adoption is driven by a more conflicting work environment in establishments with ER, then the additional controls should pick up the effect of ER. Results are reported in columns (1) and (2) of Table 3. We find little evidence in support of this channel. The effect of ER on the use of both robots and advanced digital tools remains positive and significant even when controlling for proxies of labour–management conflict.

Second, we test whether ER induces greater technology adoption by increasing labour rigidity and hence eliminating the main comparative advantage of labour vis-à-vis automated capital (Fornino and Manera 2022). Managers report whether employee representatives directly influenced management decisions on a wide range of areas, including dismissals. Indeed, ER structures are granted special prerogatives in relation to dismissals in some European countries,[17] and this may restrict the ability of employers to adjust labour. Alongside information on the strength of ER influence, the survey allows the manager to report that no decisions were actually made on a given subject matter. This unique feature of the survey allows us to disentangle the channels through which the ER influence is relevant. In fact, whenever a channel is relevant, one should observe that the case where no decision is made produces an effect that is not significantly different from the case where ER is absent. In other words, establishments with ER where no decision has been taken on a particular matter serve as a placebo group when testing the relevance of that specific channel of ER influence. The results of this empirical exercise are reported in columns (3) and (4) of Table 3 for robots and advanced digital tools, respectively. We estimate equation (1) including a set of three dummy variables that equal 1 when ER is present and—according to managers—in the three preceding years, respectively, it had no influence on layoffs because there were no dismissals, decisions on layoffs were made but ER had no or little influence on these decisions, and decisions on layoffs were made and ER had moderate or great influence on these decisions. In this model structure, the omitted category 'ER is not present' is the benchmark. Results show that the presence of ER is associated with more robot usage when ER has from none to great influence on layoffs, while the presence of ER itself when dismissal decisions were not made is not conducive to larger robot adoption. As for other advanced digital tools, even without layoffs, ER is always associated with a positive effect. These results provide weak support for the employment rigidity channel, as the positive correlation between ER and automation seems to hold regardless of the intensity of ER influence on dismissals.[18]

Third, we look at how ER may affect the adoption of advanced technologies via increasing labour costs. 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 ER in raising wages could be rather limited. First, estimates reported in columns (5) and (6) of Table 3 include a dummy variable equal to 1 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 use of advanced technologies in establishments 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 or not an ER body is present (no significant effect for other advanced digital tools).[19] In addition, we exploit specific features of European labour market institutions characterized by the coexistence of workplace ER and centralized wage-setting systems. One could argue that in more centralized wage settings, plant-level

TABLE 3
ROBOTS, ADVANCED DIGITAL TOOLS AND ER: INSTITUTIONAL FRICTIONS

	Adversarial relations		Labour rigidity		Capital–labour substitution	
	Robots	Advanced digital tools	Robots	Advanced digital tools	Robots	Advanced digital tools
Variables	(1)	(2)	(3)	(4)	(5)	(6)
ER	0.014**	0.039***			0.014**	0.036***
	(0.006)	(0.008)			(0.006)	(0.009)
Strike	0.021	0.049				
	(0.025)	(0.045)				
ER × Strike	−0.002	−0.077				
	(0.034)	(0.052)				
ER influence on layoffs: no decisions made			0.001	0.040***		
			(0.009)	(0.013)		
ER influence on layoffs: not at all/small extent			0.017**	0.030***		
			(0.007)	(0.010)		
ER influence on layoffs: moderate/great extent			0.028**	0.061***		
			(0.011)	(0.014)		
Reduced employment					−0.019***	−0.013
					(0.007)	(0.013)
ER × Reduced employment					0.005	0.015
					(0.013)	(0.020)
Observations	18,888	20,216	18,888	20,216	18,888	20,216
R-squared	0.171	0.134	0.171	0.134	0.171	0.134
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
Estimates from linear probability models with robust standard errors in parentheses. In columns (1), (3) and (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 columns (2), (4) and (6), the dependent variable is a dummy variable indicating whether the establishment uses digital tools for analysing data collected at this establishment or from other sources to improve the processes of production or service delivery. The variable 'Strike' takes value 1 if the establishment experienced an industrial action in the last three years (strikes, works-to-rule or manifestations). The variables on ER influence on layoffs are dummy variables taking value 1 when ER is present and the degree of ER influence equals each specified level (according to the manager); 'ER is absent' is the benchmark category. The variable 'Reduced employment' takes value 1 if the total number of employees in the establishment has decreased during the last three years. Establishment-level controls: plant size, plant age, multi-site, change in ownership. Workforce composition: % permanent contracts, % part-time workers. Competitive/uncertain environment: predictability of demand and competitive pressures as perceived by the manager. Manager's controls: gender and position.
***, **, * indicate $p < 0.01$, $p < 0.05$, $p < 0.1$, respectively.

wages are less responsive to the presence of ER as bargaining takes place at a higher level (industry, region or national level). Indeed, theory and some empirical studies suggest that employee representatives are less likely to engage in rent extraction activities in workplaces covered by higher-level collective bargaining agreements (Freeman and Lazear 1995; Hübler and Jirjahn 2003).[20] Using 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.1.3 of the Online Appendix show that the positive effect of ER on robots and other advanced digital tools is restricted to workplaces operating in high wage centralization environments, that is, settings in which one would expect a more limited influence of workplace ER on wages.[21]

In a recent study, Acemoglu and Restrepo (2021) show that ageing is associated with greater adoption of robots. We estimate equation (1), splitting the sample into rapidly ageing countries (above the median in terms of ageing between 1950 and 1990) and slowly ageing countries.[22] Results from this exercise are presented in columns (1)–(4) of Table A.1.4 of the Online Appendix for robots and other advanced digital tools, respectively. Interestingly, we find that while for advanced digital tools results do not differ, the effect of ER on robot usage holds only 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 where there is a scarcity of middle-age workers.

Overall, combining the evidence that originates from these empirical exercises, we conclude that the argument according to which ER induces technology adoption by increasing institutional frictions appears to be weak at most.

Complementarities between work systems and technology Finally, we investigate the channel based on the complementarity between technology and work organization. The survey reports detailed information about ER influence on workplace practices related to training, work organization and working-time management. As a first step, we exploit this information using an empirical design similar to the one adopted for dismissals, and check whether the strength of ER influence on each of these dimensions affects technology adoption.

Results are reported in columns (1)–(6) of Table 4. For both robots and other advanced digital tools, we find that the effect of ER is significantly larger (in terms of both magnitude and statistical significance) when ER has a greater influence on each dimension. In establishments where ER is present, but its influence on training, work organization and working time is null or small, the adoption of advanced technologies does not differ significantly from establishments where ER is absent. If anything, only for robot usage, the presence of ER exerting weak influence on work organization seems to be associated with a positive and significant effect. Moreover, for most of the considered dimensions, no significant effect of ER is found for the cases in which no decisions were made, highlighting the potential relevance of these channels.[23] These findings are consistent with the idea that ER may induce a larger adoption of advanced technologies by facilitating processes of organizational restructuring, which include workers' retraining as well as changes in work organization and working-time management.[24]

Related to this, we explore whether the effect of ER on the use of advanced technologies is also associated with possible complementarities between the use of such technologies and workplace practices that improve the dissemination of information across managers and employees. To analyse this aspect, we run equation (1) including alternatively: two dummy

TABLE 4
ROBOTS, ADVANCED DIGITAL TOOLS AND ER: INFLUENCE ON TRAINING AND WORK ORGANIZATION

	Robots			Advanced digital tools		
Variables	(1)	(2)	(3)	(4)	(5)	(6)
ER influence on training: no decisions were made	−0.009			0.011		
	(0.012)			(0.017)		
ER influence on training: not at all/to a small extent	0.009			0.013		
	(0.007)			(0.010)		
ER influence on training: to a moderate or great extent	0.029***			0.080***		
	(0.008)			(0.011)		
ER influence on organization: no decisions were made		−0.023**			0.002	
		(0.011)			(0.018)	
ER influence on organization: not at all/to a small extent		0.016**			0.008	
		(0.007)			(0.010)	
ER influence on organization: to a moderate or great extent		0.024***			0.084***	
		(0.007)			(0.011)	
ER influence on working time: no decisions were made			−0.011			0.013
			(0.010)			(0.015)
ER influence on working time: not at all/to a small extent			0.005			0.012
			(0.007)			(0.010)
ER influence on working time: to a moderate or great extent			0.039***			0.084***
			(0.008)			(0.011)
Observations	18,888	18,888	18,888	20,216	20,216	20,216
R-squared	0.172	0.172	0.172	0.135	0.136	0.135
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
Estimates from linear probability 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. In columns (4)–(7), the dependent variable is a dummy variable indicating whether the establishment uses digital tools for analysing data collected at this establishment or from other sources to improve the processes of production or service delivery. The variables on ER influence on training/organization/time are dummy variables taking value 1 when ER is present, and the degree of ER influence equals each specified level (according to the manager); 'ER is absent' is the benchmark category. Establishment-level controls: plant size, plant age, multi-site, change in ownership. Workforce composition: % permanent contracts, % part-time workers. Competitive/uncertain environment: predictability of demand and competitive pressures as perceived by the manager. Manager's controls: gender and position.
***, **, * indicate $p < 0.01$, $p < 0.05$, $p < 0.1$, respectively.

variables that equal 1 when managers and employees meet, respectively, on a regular and irregular basis to discuss work organization ('no meetings' being the benchmark category), and their interaction with ER; and two dummy variables that equal 1 when managers use practices of information dissemination (e.g. newsletter, website, noticeboard) on a regular and irregular basis ('no dissemination' being the benchmark category), and their interaction with ER. The results are reported in Table 5. We find that meetings and information dissemination are positively associated with the use of robots and other advanced digital tools. Moreover, these additional dimensions pick up the effect of ER. Hence, once again, the positive contribution of ER to the process of technology adoption seems to be associated with its role in favouring

TABLE 5
ROBOTS, ADVANCED DIGITAL TOOLS AND ER: PRACTICES OF EMPLOYEE INVOLVEMENT

	Robots		Advanced digital tools	
Variables	(1)	(2)	(3)	(4)
ER	0.021	0.000	0.025	0.015
	(0.022)	(0.011)	(0.032)	(0.017)
Regular-basis meetings between employees and manager	0.030***		0.215***	
	(0.010)		(0.017)	
ER × Regular-basis meetings between employees and manager	0.004		0.004	
	(0.023)		(0.033)	
Irregular-basis meetings between employees and manager	0.026***		0.105***	
	(0.010)		(0.017)	
ER × Irregular-basis meetings between employees and manager	−0.029		0.031	
	(0.024)		(0.034)	
Regular-basis information dissemination		0.014**		0.195***
		(0.006)		(0.010)
ER × Regular-basis information dissemination		0.025*		0.011
		(0.013)		(0.019)
Irregular-basis information dissemination		−0.009		0.084***
		(0.006)		(0.011)
ER × Irregular-basis information dissemination		−0.000		0.028
		(0.014)		(0.021)
Observations	18,832	18,803	20,151	20,120
R-squared	0.173	0.173	0.147	0.154
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
Estimates from linear probability models with robust standard errors in parentheses. In columns (1) and (2), 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 (3) and (4), the dependent variable is a dummy variable indicating whether the establishment uses digital tools for analysing data collected at this establishment or from other sources to improve the processes of production or service delivery. The variables on meetings between employees and the immediate managers, and the variables on information dissemination, are dummy variables, with 'no meetings' and 'no information dissemination', respectively, being the benchmark categories. Establishment-level controls: plant size, plant age, multi-site, change in ownership. Workforce composition: % permanent contracts, % part-time workers. Competitive/uncertain environment: predictability of demand and competitive pressures as perceived by the manager. Manager's controls: gender and position.
***, **, * indicate $p < 0.01$, $p < 0.05$, $p < 0.1$, respectively.

the introduction of workplace practices related to information-sharing that are somehow complementary to the adoption of such advanced technologies.

III. IDENTIFICATION THROUGH SIZE-CONTINGENT LEGISLATION: EVIDENCE FROM ITALIAN FIRMS

The Italian institutional framework

The conditional correlations presented in the preceding sections suggest a positive association between the presence of ER and the use of advanced technologies in the workplace. An obvious concern, however, relates to the endogenous formation of ER bodies. For example, there may be unobservable factors correlated with both technology adoption and the presence of ER. A reverse causal channel may also be at work: the adoption of robots and other advanced digital tools may induce workers to organize an ER body. In this section, we address these concerns by implementing an RDD that exploits size-contingent regulations governing the establishment of ER in Italy.[25]

In the Italian context, the institutions of shop-floor ER are disciplined by Law n. 300/70, also known as the *Statuto dei Lavoratori* (Workers' Statute), which in Article 19 grants the presence of unions in the workplace thorough the creation of democratically elected bodies called *Rappresentanze Sindacali Aziendali* (RSA). The latter can be established on the request of the workers, and their approval by the employer is mandatory in firms with more than 15 employees (Article 35 of the Workers' Statute). Hence the firm size threshold of 15 employees does not automatically determine the presence of a firm-level ER body. The workforce must make a formal request to the employer in order to trigger ER rights.[26] Originally, RSA could be formed and voted only by union members. Later, the Protocol Agreement signed by the Government and Social Parties on 23 July 1993 introduced an alternative ER body called *Rappresentanza Sindacale Unitaria* (RSU), which can be elected also by non-union members (more precisely, two-thirds of the representatives are elected by all the employees, and the remaining one-third are designated or elected by union members).

Both RSA and RSU are granted a series of rights to perform their function adequately. The Workers' Statute (Articles 20–27) recognizes in RSA a minimum set of rights related to the organization of assemblies and referendum, and to the publication of information material on the activities carried out by the union within the firm. Such rights have later been extended also to RSU. Moreover, following the introduction of complementary firm-level collective agreements through the same Protocol that enabled the creation of RSU, both representative bodies have been given the possibility to bargain with the employer on a set of issues pertaining directly to the organization of work, including working hours, workloads, vocational training, and the split of productivity increases between firms and workers.[27] The Protocol also makes explicit reference to the rights of RSA/RSU representatives to be informed and consulted on issues that are highly relevant for workers such as dismissals, company transfers and workplace safety.

An important feature of the Italian legislation that needs to be considered is that, alongside ER bodies, there are other labour market institutions that change discontinuously at the threshold of 15 employees. Two in particular are the most relevant. First, there is the so-called *Cassa Integrazione Guadagni Straordinaria* (CIGS) scheme, which consists of a short-time work scheme providing a wage supplement in case of interruptions or reductions of employment in firms that are either in the process of reorganization and restructuring or facing a severe economic crisis. According to Italian law, such schemes can be used only by firms above the 15 employees threshold.[28] Second, following Articles 18 and 35 of the Workers' Statute, also employment protection legislation is characterized by a size-contingent implementation. In particular, while employees with an open-ended contract in firms above the 15 employees threshold can ask for compulsory reinstatement in case of unfair dismissal (or alternatively they can opt for a severance payment amounting to 15 months' salary), the same option is not available for employees in firms below the threshold. In the latter case, it is up to the employer to choose whether to reinstate the unfairly dismissed worker or make a severance payment (for more details, see Bratti *et al.* 2021). Such discontinuity, however, has been attenuated considerably by recent legislative changes, in particular the so-called Fornero Law and the Jobs Act. The former, passed in 2012, has restricted considerably the number of cases in which workers in firms with more than 15 employees can ask for mandatory reinstatement in case of unfair dismissal. Moreover, it has diminished the amount of monetary compensation and reduced uncertainty about the duration and costs of litigation (Berton *et al.* 2017). Subsequently, the Jobs Act 2014 (Decree no. 183/2014) has reduced even further the differences among firms around the size threshold by confining, for workers hired with open-ended contracts after the law was approved, the possibility of compulsory reinstatement only to discriminatory dismissals (i.e. excluding this possibility for dismissals due to economic reasons, so-called *motivo oggettivo*). Moreover, it has introduced an out-of-court procedure that has created a strong disincentive for workers to appeal to courts in case of potentially unfair dismissals (Boeri and Garibaldi 2019).

RIL-INAPP survey: panel of Italian firms

The institutional setting described in the preceding subsection makes it possible to identify the effect of ER on technology adoption through an RDD design. To do so, we use Italian firm-level data from the RIL survey dataset (*Rilevazione Longitudinale su Imprese e Lavoro*) provided by INAPP (National Institute for the Evaluation of Public Policies). The sample of firms covered by the RIL-INAPP survey is representative of the population of both partnerships and limited liability companies operating in Italy in the private (non-agricultural) sectors. We restrict the analysis to the (panel) subsample of firms reporting information in both the 2015 and the 2018 waves of the survey, covering about 13,000 firms. In particular, we rely on lagged measures of firm size and other characteristics of the workforce (along with some other firm-level relevant information) using the 2015 wave, and compute the incidence of ER and investments in advanced technologies and ICT from the 2018 wave.

Specifically, we measure the presence of ER by using a dummy variable that equals 1 if RSU or RSA are established in the company. Investments in automation technologies are measured by means of three different dummy variables. The first is equal to 1 if the firm, over the 2015–17 period, has undertaken investments in robots. The second is equal to 1 if the firm, over the 2015–17 period, has undertaken investments in other advanced digital tools such as big data analytics, the internet of things, virtual reality and cybersecurity. The third is equal to 1 if the firm, over the 2015–17 period, has undertaken investments in more conventional ICT assets, including computers and hardware to automate and digitalize the production process. Table 6 presents a detailed description of all the variables used in the RDD analysis, and their summary statistics for the full panel sample.

Regression discontinuity analysis: a local randomization approach

Specification and assumptions The RDD is aimed at exploiting a discontinuity in treatment status (presence of ER) to identify a causal effect. The standard approach consists of estimating the model

$$y_i = \beta_0 + \beta_1\, \mathbb{1}(Size_i > c) + f(Size_i) + \varepsilon_i, \tag{2}$$

where y_i is the outcome of interest, and $\mathbb{1}(Size_i > c)$ is an indicator function that takes the value 1 for firms above the relevant size threshold (c) for triggering ER rights, and 0 otherwise. Here, $f(Size_i)$ is a continuous function in firm size on each side of c. Following the Italian legal framework in relation to workplace ER, we normalize the running variable so that for firms employing just 15 employees, the cut-off value is equal to zero. While firm size is measured in 2015, all the outcome variables are measured in 2018.

TABLE 6
MAIN VARIABLES: DESCRIPTION AND DESCRIPTIVE STATISTICS OF THE RIL-INAPP PANEL SAMPLE

Variables	Description as in the RIL-INAPP questionnaire	Mean	S.D.
ER	RSA or RSU currently exist in the firm (yes/no)	0.249	0.432
Robots	The firm has undertaken investments in robotics (yes/no)	0.013	0.113
Advanced digital tools	The firm has undertaken investments in one of the following: (i) internet of things, (ii) big data analytics, (iii) virtual reality, (iv) cybersecurity	0.376	0.488
ICT investment	The firm has undertaken investments in computers or automation-related hardware (yes/no)	0.070	0.255
Firm size	Number of employees	60.242	243.809
Firm age	Years since the firm has been established	27.789	26.438
Non-standard contracts	Share of employees with non-standard contracts (e.g. fixed term, agency, work-on-call)	0.158	0.201
Workers with tertiary education	Share of employees with tertiary education	0.169	0.278
Workers aged 50+	Share of employees aged more than 50 years old	3.279	10.517
Female manager	The CEO or the controlling manager is female (yes/no)	0.138	0.345
Exporting firm	The firm exports good or services abroad (yes/no)	0.282	0.450
Manufacturing firm	The firm operates in any of manufacturing sectors (yes/no)	0.403	0.490
Business group	The firm belongs to a national or international business group (yes/no)	0.138	0.345

Notes
RIL-INAPP panel sample, 2015–17.

Conventional continuous-based inference methods for RDD rely on non-parametric local polynomial techniques and large-sample approximations (Hahn *et al.* 2001). Given the fact that our forcing variable (size) is discrete and has few mass points (i.e. values of the variable that are shared by many units) in its support,[29] we rely on the alternative local randomization approach to regression discontinuity, which stipulates that treatment assignment may be approximated by a local random experiment near the cut-off c (Lee 2008; Cattaneo *et al.* 2015, 2016).[30]

The most important step is to select the window around the size cut-off where the presence of ER can be plausibly assumed to have been as if randomly assigned. To do this, we use the data-driven window selection procedure based on 'balance tests' of covariates developed by Cattaneo *et al.* (2015). We select the window using the information provided by relevant covariates: firm age, share of non-standard workers, share of workers with tertiary education, share of workers aged 50+ years old, presence of a female manager, and dummy variables for exporting firms, manufacturing firms, and firms that are part of a business group. All these variables are measured in 2015. In Table A.2.1 of the Online Appendix, we report the results of the window selection procedure, including randomization-based p-values from balance tests, and the covariate with minimum p-value for different windows. We analyse all symmetric windows around the cut-off between $[-1, 1]$ and $[-15, 15]$ in increments of one employee. In each window, we perform randomization-based tests (difference-in-means tests) of the null hypothesis of no treatment effect for each of the covariates. We choose 1000 simulations for the calculation of p-values in each window, and the level $\alpha^* = 0.15$ to test whether the local randomization assumption is rejected in each window, and recommend the chosen window. The output reported in Table A.2.1 indicates that the p-values are above 0.15 in all windows between the minimum window $[-1, 1]$ and $[-5, 5]$. Then the p-value drops to 0.031, below the suggested 0.15 threshold. Therefore we perform the local randomization analysis in the chosen window $[-5, 5]$.

Main results The first empirical question to address is whether there is a jump in the incidence of ER around the cut-off. Figure 6 shows clear evidence of a first-stage effect with a discontinuity in the presence of ER at the cut-off point.[31] In column (1) of Table 7, we report an average difference of 9.3 percentage points in the incidence of ER between treatment and control firms within the chosen window, which means that the probability of having an ER body for firms above the cut-off is more than double that for the control group. The null hypothesis of no treatment effect is strongly rejected with p-value 0.000.

Having documented that there is a discontinuity in the incidence of ER around the cut-off, we now turn to our outcomes of interest, that is, investments in robots and digitalization. Visual inspection of Figure 7 suggests no clear effect for robots, and potentially positive effects for advanced digital tools and ICT investments. This intuition is confirmed by the results reported in Table 7. In column (2), we report statistically insignificant effects of ER on investments in robots. The estimated 95% confidence interval ranges from -0.01 to 0.02, that is, we fail to reject differences in robot acquisitions contained within this interval with a randomization-based 5% level test. Hence the evidence is consistent with both positive and negative effects. In column (3), we report a positive average difference of roughly 6 percentage points in the acquisition of advanced digital tools in the last two years, between treatment and control units. This effect is equivalent to 12% of one standard deviation of the share of firms investing in advanced digital tools in the control group (i.e. 0.057/0.475). The null hypothesis of no treatment effect is strongly rejected with p-value 0.005. In this case, the 95% confidence interval ranges from 0.02 to 0.09, ruling out a negative effect. Finally, in column (4), we report a positive difference of 2.8 percentage points in ICT investments between treatment and

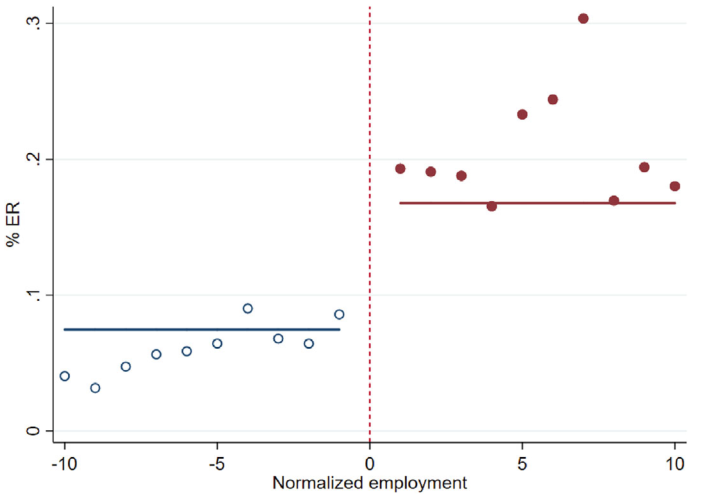

FIGURE 6. Regression discontinuity plot: incidence of employee representation (ER). *Notes*: Plots using *rdplots* of the incidence of ER using the RIL-INAPP panel of Italian firms. Normalized employment is reported on the horizontal axis, i.e. zero corresponds to the firm size threshold of 15 employees. Regression discontinuity plots are restricted to the window $[-10, 10]$, with polynomial degree 0 and a uniform kernel.

TABLE 7
RANDOMIZATION-BASED APPROACH: MAIN RESULTS (RIL-INAPP PANEL OF ITALIAN FIRMS)

	ER (1)	Robots (2)	Advanced digital tools (3)	ICT investments (4)
Point estimate	0.093	0.007	0.057	0.028
p-value	0.000	0.466	0.005	0.081
Window	$[-5, 5]$	$[-5, 5]$	$[-5, 5]$	$[-5, 5]$
Sample size treated	1157	1170	1170	1154
Sample size control	1221	1242	1242	1233

Notes
Results from the RDD estimates using a local randomization approach with analysis window $[-5, 5]$ around the cut-off and based on RIL-INAPP panel of Italian firms (local-constant polynomial approximation using a uniform kernel). In column (1), the outcome variable is a dummy variable indicating whether an ER body (either RSA or RSU) is present at the establishment. In column (2), the outcome 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 (3), the outcome variable is a dummy variable indicating whether the establishment uses advanced digital tools such as the internet of things, big data analytics, virtual reality and cybersecurity. In column (4), the outcome variable is is a dummy variable indicating whether the establishment has undertaken investments in computers or automation-related hardware. Optimal window determined based on the following covariates: firm age, share of non-standard workers, share of workers with tertiary education, share of workers aged 50+ years old, presence of female manager, and dummy variables for exporting firms, manufacturing firms and firms that are part of a business group. All these variables are measured in 2015. Models are estimated with the Stata software *rdrandinf* developed by Cattaneo *et al.* (2016).

control firms. Null effects are also rejected in this case (p-value 0.081). Given the presence of imperfect compliance, these estimates represent intention-to-treat effects.[32]

The fact that apparently ER has no effect on robot adoption, while simultaneously favouring investments in advanced digital tools and ICT, could be explained in many ways. In principle, this could be considered evidence that some of the theoretical mechanisms

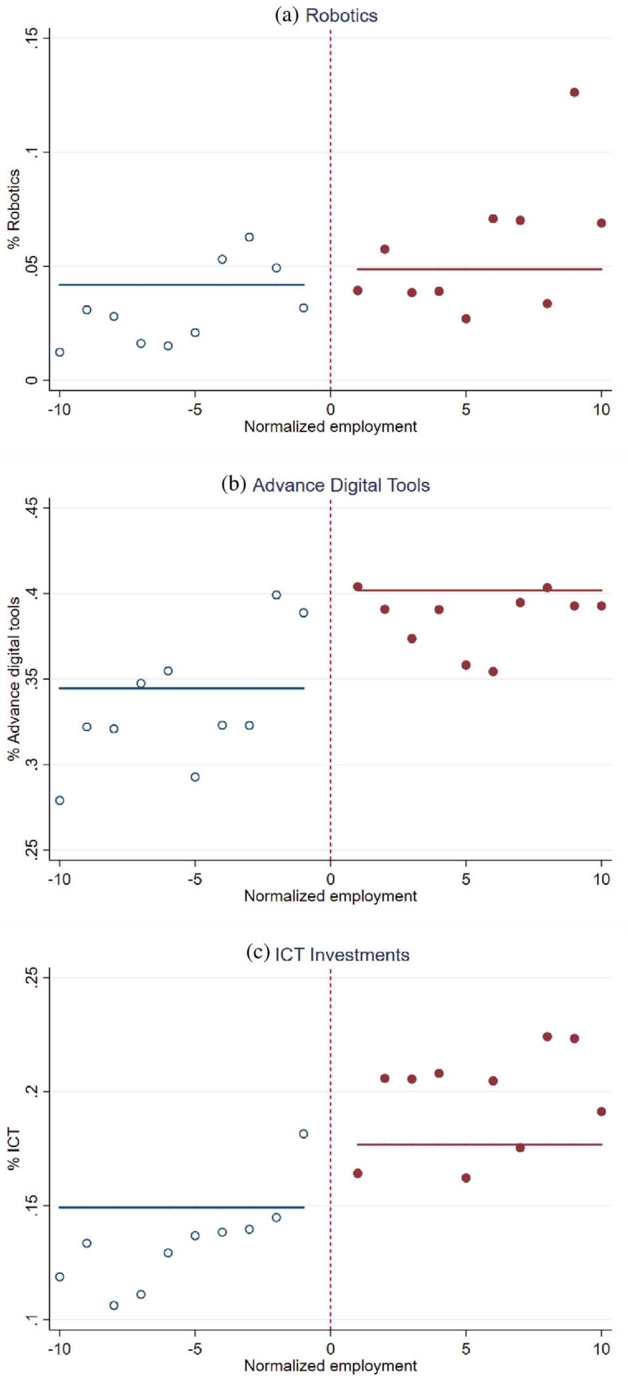

FIGURE 7. Regression discontinuity plots: investment in automation technologies and digitalization. *Notes*: Plots using *rdplots* of the firm investment in robotics (panel A), advanced digital tools (panel B) and ICT investments (panel C). Normalized employment is reported on the horizontal axis, i.e. zero corresponds to the firm size threshold of 15 employees. Regression discontinuity plots are restricted to the window $[-10, 10]$, with polynomial degree 0 and a uniform kernel.

TABLE 8
OTHER OUTCOMES: TRAINING AND INNOVATION (RIL-INAPP PANEL OF ITALIAN FIRMS)

	Training rate (1)	Process innovation (2)	Product innovation (3)
Point estimate	0.035	0.058	0.008
p-value	0.044	0.002	0.666
Window	$[-5,5]$	$[-5,5]$	$[-5,5]$
Sample size treated	1030	1170	1170
Sample size control	1114	1242	1242

Notes
Results from the RDD estimates using a local randomization approach with analysis window $[-5,5]$ around the cut-off (local-constant polynomial approximation using a uniform kernel). Estimates based on RIL-INAPP panel of Italian firms. In column (1), the training rate is defined as the ratio between the number of employees participating in training activities and total employment. In column (2), the outcome is a dummy variable equals to 1 if the firm undertook innovations affecting the production process in the last 3 years, and 0 otherwise. In column (3), the outcome is a dummy variable equals to 1 if the firm undertook innovations affecting its products/ services in the last 3 years, and 0 otherwise. Optimal window determined using the following covariates: firm age, share of non-standard workers, share of workers with tertiary education, share of workers aged 50+ years old, presence of female manager, and dummy variables for exporting firms, manufacturing firms and firms that are part of a business group. All these variables are measured in 2015. Models are estimated with the Stata software *rdrandinf* developed by Cattaneo *et al.* (2016).

discussed above are more relevant for the adoption of intangible automated capital as opposed to tangible. For instance, this could be the case if the organizational practices induced by ER (e.g. information transmission) are more complementary to the use of digital tools than to the use of robots. At the same time, however, the lack of evidence on robots could also be a by-product of the specific context under investigation. The features of the Italian legislation, in fact, force us to conduct the regression discontinuity analysis on firms that are relatively small, whereas robots tend to be used mainly by large firms.[33] This may limit our ability to quantify clearly the impact of ER on robots (but not on other advanced digital tools whose use is common also among relatively small firms). Some insights that this interpretation can be correct come from robustness checks reported below, which show that when we consider firms of larger size, the effects of ER become positive and qualitatively similar across all types of automated capital.

Organizational outcomes, employment changes and skill composition In Table 8, we look at organizational outcomes that may be complementary to the use of advanced technologies, such as training, process and product innovation. In column (1), we report a significantly positive effect of ER on the training rate (3.5 percentage points) around the cut-off, that is, a 10% increase in relation to the mean training rate in the control group. While there are no statistically significant differences in terms of product innovation, we find a increase of roughly 6 percentage points in the likelihood of process innovation. This is equivalent to a 20% increase in process innovation self-reported by managers compared to the control group. Taken together, our findings suggests that the adoption of advanced technologies is accompanied by complementary organizational changes and investments in workforce training.

As discussed in Section I, one way to distinguish between the different channels through which ER may exert a positive effect on technology adoption is to look at changes in employment and skill composition. If the presence of ER increases labour costs and induces factor price distortions and allocation inefficiencies, then one should observe that the greater use of advanced technologies results in layoffs, particularly among production and

TABLE 9
EMPLOYMENT OUTCOMES (RIL-INAPP PANEL OF ITALIAN FIRMS)

	Employment growth 2017–18 (1)	Employment growth 2015–18 (2)	Hiring rate (3)	Separation rate (4)	Quit rate (5)	Layoff rate (6)	Vacancy rate (7)
Point estimate	0.008	−0.013	−0.001	0.000	0.002	−0.007	−0.003
p-value	0.129	0.378	0.934	0.994	0.521	0.006	0.160
Window	[−5, 5]	[−5, 5]	[−5, 5]	[−5, 5]	[−5, 5]	[−5, 5]	[−5, 5]
Sample size treated	1060	1060	1049	1052	1059	1058	1060
Sample size control	1116	1116	1101	1104	1116	1114	1116

Notes
Results from the RDD estimates using a local randomization approach with analysis window [−5, 5] around the cut-off (local-constant polynomial approximation using a uniform kernel). Outcome variables: (1) log change in employment (period 2017–18); (2) log change in employment (period 2015–18); (3) hiring rate is defined as the ratio between job hires in 2017 and total employment in December 2016; (4) separation rate is the ratio between total separations in 2017 and total employment in December 2016; (5) quit rate is the ratio between voluntary quits in 2017 and the sum of total employment and vacancies in 2018; (6) layoff rate is the ratio between dismissals in 2017 and total employment in December 2016; (7) vacancy rate is defined as the ratio between the number of current job vacancies and the sum of total employment and job vacancies. Estimates based on RIL-INAPP panel of Italian firms. Optimal window determined using the following covariates: firm age, share of non-standard workers, share of workers with tertiary education, share of workers aged 50+ years old, presence of female manager, and dummy variables for exporting firms, manufacturing firms and firms that are part of a business group. All these variables are measured in 2015. Models are estimated with the Stata software *rdrandinf* developed by Cattaneo *et al.* (2016).

less-educated workers. Moreover, Presidente (2020) argues that the increase in worker bargaining power associated with ER institutions will lead firms to introduce robots in production lines to reduce hold-up threats, reducing employment opportunities. On the contrary, ER may improve information flows and mitigate coordination failures within firms, fostering the utilization of workplace practices that are complementary to advanced technologies. In this case, the utilization of robots and advanced digital tools may not necessarily involve layoffs.Consistent with this view, recent studies have shown that ER may contribute to reduce the job displacement effects of technological change by smoothing workers' transitions from routine to abstract tasks, and facilitating retraining and skill upgrading within the firms (Dauth *et al.* 2021; Battisti *et al.* 2021). Finally, recent studies show that firms introducing advanced technologies may actually expand total employment (Aghion *et al.* 2021; Hirvonen *et al.* 2021).

In Table 9, we report RDD estimates considering a broad set of employment outcomes, including employment growth, hiring and separation rates, and vacancies rates. Results are statistically insignificant across the board, except for a significant reduction in the layoff rate. Moreover, in Table 10, we look at changes in the composition of the workforce in terms of occupations, education, age and share of permanent contracts. We do not observe significant discontinuities in the composition of the workforce along these dimensions.

Falsification and validation analysis We conduct a series of falsification tests to assess the validity of our local randomization RDD.

First, we check for systematic differences in terms of covariates between units below and above the cut-off. More precisely, we test the hypothesis that the treatment effect is zero for each covariate. We consider all the variables used as part of the window selection process. We perform the analysis in the same way as for the main outcomes, using the window [−5, 5].

TABLE 10
WORKFORCE COMPOSITION (RIL-INAPP PANEL OF ITALIAN FIRMS)

	Production worker share (1)	Clerical worker share (2)	Manager share (3)	Low education share (4)	Medium education share (5)	High education share (6)	Young worker share (7)	Old worker share (8)	Permanent worker share (9)
Point estimate	0.012	−0.016	0.005	0.005	0.001	−0.006	−0.003	0.004	−0.008
p-value	0.374	0.241	0.073	0.757	0.946	0.522	0.403	0.241	0.255
Window	[−5, 5]	[−5, 5]	[−5, 5]	[−5, 5]	[−5, 5]	[−5, 5]	[−5, 5]	[−5, 5]	[−5, 5]
Sample size treated	1060	1060	1060	1060	1060	1060	1060	1060	1060
Sample size control	1116	1116	1116	1116	1116	1116	1116	1116	1116

Notes
Results from the RDD estimates using a local randomization approach with analysis window [−5, 5] around the cut-off (local-constant polynomial approximation using a uniform kernel). Outcome variables defined as the share of different worker categories in total employment. Estimates based on RIL-INAPP panel of Italian firms. Optimal window determined using the following covariates: firm age, share of non-standard workers, share of workers with tertiary education, share of workers aged 50+ years old, presence of female manager, and dummy variables for exporting firms, manufacturing firms and firms that are part of a business group. All these variables are measured in 2015. Models are estimated with the Stata software *rdrandinf* developed by Cattaneo *et al.* (2016).

Results are reported in Table A.2.2 and Figure A.2.1 of the Online Appendix. Reassuringly, we do not find evidence of treatment effects for any of these characteristics.

Second, we analyse the density of the forcing variable within our selected window $[-5, 5]$, that is, whether the number of establishments just above the cut-off is similar to the number of establishments just below it. Sorting around the cut-off may occur if firms manipulate their size in order to block employees' attempts to trigger ER rights. The numbers of control firms immediately below the cut-off (1242) and treatment firms above the cut-off (1170) are slightly unbalanced. However, a binomial test that the probability of being treated is 0.5 does not reject the null (p-value 0.148), indicating no evidence of sorting around the cut-off in the chosen window (Cattaneo *et al.* 2017).[34]

Third, we consider the sensitivity of the results to our window choice. We replicate the local randomization analysis for windows both smaller and larger than our selected window. We consider smaller and larger windows $[-3, 3]$, $[-7, 7]$, $[-9, 9]$ and $[-11, 11]$. As discussed by Cattaneo *et al.* (2015), the analysis of a larger window is useful to understand whether the results continue to hold under departures from local randomization assumptions. The analysis of smaller windows, instead, may uncover heterogeneous effects within the originally selected window. Table A.2.3 of the Online Appendix presents the results from this exercise. Overall, our main results hold when we consider larger windows. Moreover, the effect on robot acquisitions becomes significantly positive for larger windows. This, as suggested above, is not surprising considering that robot usage is highly concentrated among larger firms, and our baseline regression discontinuity analysis is restricted to relatively small firms. Such results would indicate that in large firms, the effect of ER on robots and other advanced digital tools is qualitatively similar. It is worth noting, however, that our identification assumptions hold only within the optimal window.

Finally, we consider placebo cut-off values at which the probability of treatment should not change. We expect not to find any effect at these 'fake' cut-offs. To circumvent misspecification problems, estimates include only observations from the same side of the true firm size threshold. We consider $[-5, 5]$ windows with $c = 10$, where all units below and above the fake cut-off belong to the control group, and cases involving all treated units ($c = 25, 35$). In the case of 10 employees, estimates are positive but generally much smaller. In the case of 25 or 35 employees, estimates are statistically insignificant (see Table A.2.4 of the Online Appendix).

Additional robustness checks: donut-hole, fuzzy RDD and linear adjustment First, we account for potential measurement error in the forcing variable (firm size). Two sources of measurement error in our setting are heaping (e.g. managers may report round employment figures) and lack of detailed information on part-time and temporary contracts (Bratti *et al.* 2021).[35] For this reason, in panel A of Table 11, we report estimates from a donut-hole specification in which we exclude firms with 15 employees. This donut approach also accounts for potential sorting around the cut-off. This is a demanding exercise in the context of our local randomization design, as we are already including firms within a very small bandwidth around the cut-off. Our donut-hole estimates, however, lead to very similar conclusions. The only exception is the estimate for the training rate, which is no longer statistically significant.

Second, as mentioned above, the firm size threshold of 15 employees does not determine perfectly treatment (ER presence) as workplace ER bodies are established only if requested by the firm's workforce. However, the threshold creates a discontinuity in the probability of receiving treatment. To account for imperfect compliance with the treatment, in panel B of Table 11 we also report estimates from a donut-hole/fuzzy RDD using as an instrument for ER status the 15-employee threshold. Results point in the same direction as our baseline RDD

TABLE 11
ADDITIONAL ROBUSTNESS CHECKS: FUZZY RDD, DONUT-HOLE AND LINEAR SPECIFICATION (RIL-INAPP PANEL OF ITALIAN FIRMS)

	ER	Robots	Advanced digital tools	ICT investments	Training rate	Process innovations
A. Donut-hole specification						
Point estimate	0.120	−0.001	0.040	0.039	0.027	0.049
p-value	0.000	0.917	0.055	0.024	0.166	0.018
Window	[−5, 5]	[−5, 5]	[−5, 5]	[−5, 5]	[−5, 5]	[−5, 5]
Sample size treated	829	835	835	824	724	835
Sample size control	1221	1242	1242	1233	1114	1242
B.Donut-hole/fuzzy RDD						
Point estimate		−0.013	0.317	0.309	0.188	0.379
p-value		0.861	0.091	0.035	0.233	0.036
Window		[−5, 5]	[−5, 5]	[−5, 5]	[−5, 5]	[−5, 5]
Sample size treated		835	835	824	724	835
Sample size control		1242	1242	1233	1114	1242
C. Linear adjustment ($p = 1$)						
Point estimate	0.046	0.015	0.010	−0.018	0.045	0.054
p-value	0.000	0.061	0.619	0.239	0.013	0.005
Window	[−5, 5]	[−5, 5]	[−5, 5]	[−5, 5]	[−5, 5]	[−5, 5]
Sample size treated	1157	1170	1170	1154	1030	1170
Sample size control	1221	1242	1242	1233	1114	1242

Notes
Results from the RDD estimates using a local randomization approach with analysis window $[-5, 5]$ around the cut-off. Estimates based on RIL-INAPP panel of Italian firms. Panel A: estimates from a donut-hole specification, excluding firms employing 14–16 employees. Panel B: fuzzy RDD estimates where ER is the endogenous treatment variable (two-stage least squares statistic). Panel C: estimates using a local-linear ($p = 1$) polynomial transformation. Outcome variables defined as in Table 7. Optimal window determined using the following covariates: firm age, share of non-standard workers, share of workers with tertiary education, share of workers aged 50+ years old, presence of female manager, and dummy variables for exporting firms, manufacturing firms and firms that are part of a business group. All these variables are measured in 2015. Models are estimated with the Stata software *rdrandinf* developed by Cattaneo *et al.* (2016).

estimates. In this case, effects are larger, but their interpretation is different as inference is conditioned on the subgroup of compliers, that is, those firms for which the presence of ER bodies is determined by the size threshold. Finally, in panel C we also report estimates from a model using a linear adjustment (polynomial degree 1). In practice, this transformation is aimed at relaxing the assumption, usually imposed in a local randomization context, that the outcome response to the treatment is a constant of the running variable within the selected window. In this case, the first-stage effect on the probability of ER is significantly positive, though smaller in magnitude than our baseline estimates based on an untransformed (constant) model. Our baseline results for advanced digital tools and ICT investments are not robust to the use of a linear transformation. We find, however, a positive and weakly significant effect on the acquisitions of robots. As discussed by Cattaneo *et al.* (2017), linear adjustment in the local randomization framework should be used cautiously. Given the small number of units used near the cut-off, the fitted slope is very sensitive to outliers, making estimates and p-values very unstable. The constant model should be less severely affected by this problem.

Confounding regulations As discussed previously, two other important labour market institutions change discontinuously at the threshold of 15 employees in Italy: employment protection legislation and short-time work schemes (CIG). These regulations may confound the effect of ER on a firm's technological choices. We tackle this issue in several ways. First, in relation to employment protection, it is worth noting that recent labour market reforms in Italy have notably lessened the level of employment protection above the threshold of 15 employees (Berton *et al.* 2017; Boeri and Garibaldi 2019). Moreover, our analysis is restricted to the policy-on period (2015–18) in which both reforms, that is, the Fornero Law (2012) and the Jobs Act (2014), had already been implemented.[36] No other major regulatory changes affecting firms below and above the 15 employees cut-off occurred differently during the period under consideration.[37] To further account for confounding regulations, we exploit two questions available in the survey reporting information about the use of CIG and effects of the Jobs Act at the firm level. More precisely, we estimate the model excluding firms that reported use of CIG in 2015. In addition, we also exclude firms that, according to their managers, modified their recruitment plans as a result of the Jobs Act. One could assume plausibly that firing restrictions were particularly binding for this group of firms before 2015.[38] Results are remarkably similar, suggesting that other regulations are not driving our main results (see Table A.2.5 of the Online Appendix).[39]

IV. Conclusions

Our study shed light on the interplay between labour institutions and the use of advanced technologies in the workplace. We found no evidence that ER discourages technology adoption. Using establishment-level data from 26 European countries, we document a positive correlation between shop-floor ER and the utilization of robots and other advanced digital tools. Additional analysis suggests that the more frequent use of advanced technologies in establishments with ER seems to be driven neither by adversarial labour–management relationships, nor by ER-induced labour rigidity. ER seems to favour certain work systems and practices, such as training, working-time management and information-sharing, that are complementary to the adoption of new technologies.

We also conducted a quantitative case study, based on a regression discontinuity design over a panel of Italian firms. In our preferred estimates from a local-constant model, we found no evidence of ER effects on robot acquisitions. In turn, ER raises the acquisition of advanced digital tools and ICT significantly. We also found an increase in the training rate and greater incidence of process innovation with no employment effects around the cut-off. Taken together, these results suggest that granting institutionalized channels of employee voice on average may favour, and at a minimum does not harm, the adoption of advanced technologies in the workplace.

The documented effect of ER on advanced technologies may be consistent with a conventional capital–labour substitution mechanism, as greater workers' bargaining power may result in higher labour costs. We found some indirect evidence suggesting that this is not a first-order channel. Our descriptive analysis of European establishments showed that the effect of ER on the utilization of advanced technologies is present only in highly centralized wage-setting environments, where the scope for influencing wages at the shop floor is more limited. Moreover, our RDD estimates using Italian firms show no indication of major changes in both the level and composition of employment around the cut-off as the labour cost channel would predict.

We acknowledge some limitations of our regression discontinuity analysis. First, the lack of time variation in policy rules regulating Italian ER bodies makes our strategy vulnerable to potential measurement errors in the running variable and the existence of other policy discontinuities hitting Italian firms at the 15 employees cut-off (e.g. employment protection legislation, short-time work schemes). The extensive battery of validation and robustness checks provided in the paper mitigate yet do not eliminate these concerns. For instance, the Jobs Act reduced the level of employment protection above the 15 employees threshold by introducing the open-ended contract (*contratto a tutele crescenti*), but only in the case of workers hired after the legislation came into force. Thus a substantial share of the workforce (i.e. older workers) remained under the previous and stricter EPL regime. In settings in which firms are less free to fire, they might have an incentive to implement technologies preserving the productivity of older workers. Therefore we cannot discard that our estimates represent the joint effect of employment protection and ER. Second, in the presence of non-monotonic treatment effects, the average treatment effect estimated in the paper may obscure the actual heterogeneous impact of ER on the adoption of new technologies. In particular, firms may sort into treatment (ER status) based on the anticipated (heterogeneous) gain from worker voice institutions. Finally, our study exploited exogenous variation in the probability of establishing ER bodies among relatively small firms in Italy. This may explain the lack of significant effects of ER on investments in robotics, usually concentrated among large firms.

Overall, the results of the paper contribute to contemporary policy discussions in relation to the governance of robotization and digitalization (Goos 2018; Goldfarb *et al.* 2019; Autor *et al.* 2020). The growing awareness about the benefits and costs of such advanced technologies has indeed spurred many academic and public policy debates. One important concern relates to the potential role of public policy in helping firms to internalize the external costs created by their technological choices and redirecting adoption away from 'so-so technologies' that replace workers but generate very small productivity gains (Acemoglu and Restrepo 2019). Our study may contribute to rationalize documented differences in the employment effects of automation technologies across countries, showing that job displacements effects tend to be stronger in the USA (Acemoglu and Restrepo 2020) than in European countries (Dauth *et al.* 2021; Hirvonen *et al.* 2021; Aghion *et al.* 2021). These differences may be attributed to labour market institutions, particularly in relation to the incidence of worker voice arrangements. Indeed, our paper suggests that workplace ER could be an important component of the governance strategy shaping the future of work. By facilitating workforce upskilling and stimulating richer job designs and other workplace practices that complement advanced technologies, ER may favour processes of technological upgrading that go hand-in-hand with improved working conditions and reduce exposure to automation risk for workers.

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NOTES

1. For recent applications of the local randomization approach, see Zimmermann (2021) and Brugarolas and Miller (2021).
2. The rapid diffusion of robots and modern digital technologies has led many authors to investigate the effects of these technologies on labour along different dimensions, such as skill polarization (Acemoglu and Restrepo 2018), wage inequality (Barth *et al.* 2020) and employment (Acemoglu and Restrepo 2020; Bessen

et al. 2019, 2020; Graetz and Michaels 2018; Carbonero *et al.* 2020; Chiacchio *et al.* 2018; Barbieri *et al.* 2020; Hirvonen *et al.* 2021; Aghion *et al.* 2021; Battisti and Gravina 2021).

3. Few recent studies analyse the effect of other labour market institutions on automation technologies, including minimum wages (Fan *et al.* 2021; Deng *et al.* 2021) and employment protection (Koch *et al.* 2021).
4. Using firm-level data from Portugal, Martins (2019) shows that shop-floor ER fosters investments in training and firm productivity, and has limited effects on wages, given the predominance of sectoral collective agreements.
5. Along these lines, Acemoglu and Restrepo (2021) report country-level evidence showing that greater unionization rates are associated with higher robot adoption, suggesting that the correlation may be driven by the fact that unions raise labour costs.
6. Notice, however, that whether unions oppose flexible employment is controversial. Recent research has showed that unions may favour the use of temporary workers (Devicienti *et al.* 2018) and increase flexibility along other margins, such as working-time arrangements (Burdin and Pérotin 2019).
7. 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 1973 [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 1967 [1867]). More recently, Caprettini and Voth (2020) provide historical evidence supporting a reverse causal relationship: labour-saving technologies caused social unrest in 1830s England.
8. Obviously, such an argument holds under the condition that robots are not exposed to the same risk of hold-up as non-automated capital. Otherwise, as discussed above, the stronger bargaining power of workers should discourage capitalists from investing in robots.
9. In this respect, Wu *et al.* (2019) show that data analytics technologies play an important role in strengthening firms' search capabilities for acquiring diverse knowledge from different sources.
10. In line with this view, Gihleb *et al.* (2020) document that the introduction of robots is 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.
11. The original dataset covers 28 countries. However, we exclude from the analysis two countries (Malta and Cyprus) due to the relatively small number of observations (less than 200). Thus our final sample covers 26 countries.
12. A wide range of estimates are available in the literature. Deng *et al.* (2021) estimate that roughly 2% of all German plants (and 8% of manufacturing plants) used robots in 2018. Koch *et al.* (2021) report that 20% of Spanish manufacturing plants used robots in 2014. Using a sample of Chinese firms, Cheng *et al.* (2019) estimate that 9% of firms used robots in 2015. Finally, based on a recent survey of US firms, Cheng *et al.* (2019) report an average use rate of robots of 1.3% for all plants, and above 14% for several manufacturing sectors. The comparison with other studies reporting firm-level measures of robot usage should consider that our survey does not cover establishments employing fewer than ten workers.
13. A country's policies might favour both ER and investment in robots and advanced digital tools in certain industries. To account for this possibility, we also control for country × industry effects, obtaining similar results.
14. We obtain qualitatively similar estimates when average marginal effects are obtained from probit models. Results are available on request.
15. Notice that in these regressions, the dummy variables for the presence of different ER bodies are not mutually exclusive, i.e. two or more types of ER may be present at the same time in the same establishment. Nevertheless, unreported regressions run after excluding establishments with more than one body produce very similar results.
16. Unfortunately, we cannot distinguish between different types of industrial actions, which in turn may have different effects on capital investments (Moene 1988).
17. For example, companies are usually required to inform and consult employee representatives in case of collective redundancies.
18. An additional test of this mechanism can be obtained by exploiting the cross-country heterogeneity in employment protection legislation (EPL). In fact, if the employment rigidity argument is correct and there exists some complementary between EPL and ER (e.g. ER may act as a shop-floor rule enforcement mechanism of EPL), then one should expect the effect of ER on technology adoption to be greatest in countries where EPL is more stringent. Along these lines, we estimate equation (1) splitting the sample according to a country-level OECD index of EPL stringency (see Table A.1.2 of the Online Appendix). Contrary to the employment rigidity argument, we find that the effect of ER on robot usage is present only in the low EPL subsample. Moreover, with reference to advanced digital tools, the effect of ER holds the same regardless of the level of the employment protection.
19. As long as production efficiency rises sufficiently after adoption, expanding employment could still be consistent with a process of capital–labour substitution driven by high wages. Therefore this evidence should be taken with caution.
20. Evidence on weaker wage effects of works councils in workplaces covered by collective agreements is somewhat mixed (Jirjahn 2017). Recent studies on shop-floor ER in Portugal and German co-determination show no effects on wages (Martins 2019; Jäger *et al.* 2014).

21. Our variable of wage centralization is computed at country–industry level in order to better exploit the granularity of the data, even if much of the variability in this variable comes from cross-country heterogeneity. (Specifically, the average standard deviation of the variable computed at a country–industry level is 0.284, but when the variable is computed at a country level, its average standard deviation is 0.049.) In unreported regressions, however, we verified that the estimation results obtained on subsamples of 'decentralized' versus 'centralized' countries, regardless of the industry, are virtually unchanged with respect to those reported in Table A.1.3 of the Online Appendix.
22. 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.
23. Notice, however, that the effect of ER on robots is negative when no decision on work organization was made.
24. Previous works suggest that robot usage is often associated with organizational restructuring aimed at improving the health and safety of the workers (e.g. Gihleb *et al.* 2020). To check this, and in particular whether ER favours similar improvements in working conditions, we split the sample depending on the past quality of the task environment. In particular, we exploit individual-level information taken from the European Working Condition Survey (EWCS) 2005 to measure the incidence of 'bad tasks', which involve: (i) tiring or painful positions; (ii) lifting or moving people; (iii) repetitive hand or arm movements. We then regress the use of robots and advanced digital tools against ER in subsamples characterized by a relatively high/low incidence of bad tasks (see Table A.1.5 in the Online Appendix). Results show that the positive association between ER and robot usage remains significant only in industries that in the past were characterized by a high incidence of bad tasks. This is consistent with ER favouring the adoption of robots targeted explicitly to replace unhealthy and unpleasant jobs (see Genz *et al.* (2019) for similar results in the German context). No difference, instead, emerges with respect to other advanced digital tools.
25. Similar size-contingent legislation exists in other European countries as well (for details, see Fulton 2020; Adams *et al.* 2017). However, it is difficult to take into account adequately all nuances of national laws. Besides, in ECS data, the forcing variable (establishment size) and the use of technology are measured contemporaneously, which prevents a clear identification of the effect associated with ER. Hence we prefer to limit our causal analysis to the Italian case. As a complementary exercise in Online Appendix Section A.3, we replicate the RDD analysis for all EU countries where size-contingent legislation is in place. The results are broadly consistent with those presented in this section.
26. Article 35 limits the application of Article 19 to production units with more than 15 employees, where production units means headquarters, establishments, branches, offices or independent departments. Later, the jurisprudence has extended this concept, suggesting that autonomous company divisions performing instrumental and/or auxiliary functions with respect to the final aims of the company should not be considered as independent production units (*Cass. civ., sez. Lavoro* 04-10-2004, n. 19837; *conformi Cass. civ., sez. Lavoro*, 14-06-1999, n. 5892—RV527459 ; *Cass*. 19 *luglio* 1995 n. 7848 *ed ivi ulteriori citazioni*). Therefore the firm as a whole can be considered as a good first approximation for the size-contingent application of Article 19.
27. The logic inspiring the Italian system of two-tier collective bargaining is similar to the one of mixed systems that is common in many Western European countries. First, at the industry/national level, unions and firm representatives bargain on broader matters related to wages, working hours, and health and safety conditions. Then at the firm/local level, the employer and RSA/RSU members, in conjunction with local union representatives within the framework of the national collective agreement adopted by the firm, negotiate on issues that are delegated by first-level agreements and concern specific aspects of work organization.
28. At the same time, all firms, independently of their size, have access to the so-called *Cassa Integrazione Guadagni Ordinaria* (CIGO) scheme, aimed at helping firms facing a temporary reduction of activities due to causes and/or market events not attributable to the employer's decisions.
29. We count 13,148 observations with non-missing values of the forcing variable. However, the variable is discrete and has mass points, with 629 unique values. This would be the effective number of observations used in continuity-based regression discontinuity methods. Traditionally, researchers have dealt with this problem by clustering standard errors by the running variable (Lee and Lemieux 2010; Lee and Card 2008). However, a recent study recommends against this procedure (Kolesár and Rothe 2018).
30. For practical implementation, we use the functions *rdwinselect* and *rdrandinf*, part of the *rdlocrand* package developed by Cattaneo *et al.* (2015).
31. Figure 6 also makes clear that the discontinuity in the incidence of ER bodies is not sharp, due to the presence of non-compliers. For this reason, we report additional fuzzy RDD estimates below.
32. One issue that could potentially affect our result is firm selection. Indeed, if firms with strong ER are more likely to exit the market in the absence of technology adoption than firms without ER, then this could bias the analyses towards the results of our RDD estimates. To check for this, we exploit one question in the RIL-INAPP 2018 survey that asks if the firm is active or not active, and if the latter, whether it has activated legal procedures to exit the market (e.g. *liquidazione*, *fallimento*, *chiusura*). Thus we build a dummy variable that equals 1 if the firm has activated any such procedures in 2018, and for firms with less than or equal to 20 employees, we regress this variable against the presence of ER in 2015. Results suggest that, controlling for ICT adoption (plus other baseline controls measured in 2015), ER is not significantly correlated with exit. The same result holds also when we restrict the analysis to firms that did not invest in digital technologies in 2015. Thus biases due to firm selection do not seem to be a major concern in our analysis.

33. Specifically, in our data, robots are adopted by less than 10% of small firms (i.e. those employing fewer than 50 employees), while the share of large firms (i.e. with more than 250 employees) adopting robots is roughly 30%. Digital tools are adopted by about 40% of small firms and by about 75% of large firms.
34. We also perform the test for the smoothness of a discrete running variable developed by Frandsen (2017). When using the whole sample, the test rejects the null hypothesis of no manipulation in the running variable (p-value 0.009), but when we drop observations at the cut-off value, the null is not rejected (p-value 0.186). In the next subsubsection, we report results from a donut-hole specification excluding firms employing 15 employees.
35. In Italian labour law, the 15-employee threshold is calculated on a full-time-equivalent basis, with part-time workers counted in proportion to the number of worked hours, and temporary staff according to the average number of months worked in previous years.
36. To be precise, the section of the Jobs Act referring to firing costs was issued in December 2014 and came into force in March 2015. Hence its effects may not be captured fully in the 2015 RIL wave.
37. Italy also experimented with different types of hiring subsidies during this period (Sestito and Viviano 2018). To our knowledge, however, eligibility for these subsidies does not change discontinuously at the 15 employees threshold. Roughly 19% of firms in our sample report having used these subsidies. Our main findings reported in Table 7 are robust to the exclusion of these firms.
38. Roughly 20% of firms within our selected size window modified recruitment plans as a result of the Jobs Act (8% of firms in the whole sample), and 5% of firms reported using CIG (2% of the whole sample).
39. One could further investigate the potential confounding effect of labour market reforms on technology adoption by following a difference in regression discontinuities design. Using this approach and the 2010–15 RIL waves, Bratti *et al.* (2021) show that the Fornero Law increases the number of trained workers for eligible firms after the reform. Unfortunately, we cannot rely fully on this approach as information on most advanced technologies is available only for the 2018 RIL wave. We can implement a difference in discontinuities design only for ICT investments (*Dotazioni informatiche: computer, hardware per automazione e digitalizzazione dei processi produttivi*) as information was collected in a consistent manner over the period 2007–18, i.e. before and after the reform. Our estimates (available on request) do not suggest a differential increase in ICT investments in the post-reform period for firms above the 15 employees threshold.

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SUPPORTING INFORMATION

Additional Supporting Information may be found in the online version of this article:

A.1 Correlation between ER and advanced technologies: additional results from EU workplaces
A.2 RD analysis using RIL-INAPP panel of Italian firms: robustness and validation checks
A.3 Complementary RDD analysis: EU workplaces

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