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## Robots, Digitalization, and Worker Voice

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# Robots, Digitalization, and Worker Voice

Filippo Belloc      Gabriel Burdin      Fabio Landini\*

## Abstract

The interplay between labor institutions and the 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 20000 European establishments, this paper documents a positive association between shop-floor employee representation (ER) and the utilization of these advanced technologies. We extensively dig into the potential mechanisms driving this correlation by exploiting rich information on the *de facto* role played by ER bodies 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 cutoff, although the results are sensitive to the type of technology and specification choices. We also document positive effects on training intensity and process innovation and no evidence of employment losses or changes in the composition of employment. Taken together, our findings cast doubts on the idea that ER discourages technology adoption. On the contrary, ER seems to influence work organization and certain workplace practices in ways that may enhance the complementarity between labor and new advanced technologies.

*JEL Classification:* J50, O32, O33

*Keywords:* Automation, Robots, Digitalization, Unions, Employee Representation, Labor Market Institutions

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# 1 Introduction

The use of advanced technologies at the workplace has significantly improved 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 extensively investigated in the literature, especially with reference to their potential implications for labor 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 labor 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), i.e. 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 refer to a broad set of new technologies for analyzing data through the production process on the basis of automated information gathering and analysis (e.g. big data analytics, 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 rises 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 labor 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, 2021; Presidente, 2020). Alternatively, ER may enable the adoption of advanced technologies through its effect on information flows, labor-management cooperation and work organization (Freeman and Lazear, 1995). In particular, the more ER favors work systems that allow for information sharing, 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 main aim of this paper is to provide evidence that helps to disentangling 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 (2019). Such correlational analysis allows us to obtain preliminary descriptive evidence about this relationship that spans across 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 technology adoption through a case study based on a regression discontinuity design (RDD). In particular, our identification approach rests on size-contingent labor 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. To focus 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).<sup>1</sup>

We obtain the following results. At the descriptive level we find no evidence of a negative association between ER and the use of robots and advanced digital tools. Rather, in all cross-country specifications we obtain a positive and statistically significant effect. This holds regardless of the extent of ER involvement in dismissal decisions at the 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 some 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 estab-

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<sup>1</sup>For recent applications of the local randomization approach, see Zimmermann (2021) and Brugarolas and Miller (2021).

lishments located in rapidly ageing countries, i.e. precisely in environments where the relative scarcity of middle age 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 employee representation on wages.

When we zoom our focus on Italy and look at the causal effect of ER bodies on the use of robots and advanced digital tools for firms around the size cutoff, 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 channeled through ER bodies rises the acquisition of advanced digital tools by 6 percentage points. This effect is equivalent to a 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). Estimates from a local-linear model, arguably more sensitive to outliers given the small number of units used near the cutoff, show a significantly positive effect of ER on robotics and no impact on other digital technologies. Overall, our RDD estimates provide no evidence that ER discourages technology adoption. We find that worker voice, if anything, induces greater investments in these advanced technologies.

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 higher training rates and process innovation. As part of our RDD, we account for other confounding regulations affecting firms around the cutoff 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 favored by ER than by pure capital-labor substitution.

Our paper is most closely related to two streams of literature. First, our study relates to theoretical and empirical works on the relationship between technology and labor. Rather than focusing on the labor market effects of advanced technologies, we study whether labor market institutions aimed at fostering worker voice shape their adoption in the first place.<sup>2</sup>

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<sup>2</sup>The rapid diffusion of robots and modern digital technologies has led many authors to investigate the effects of these technologies on labor along different dimensions, such as skill polarization (Acemoglu and Restrepo,

While some recent studies have begun to address similar issues, they rely on *de jure* measures of labor rights and employee representation 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., 2019; Zolas et al., 2020; 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. 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 re-training 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 the adoption advanced technologies. Rather, it favors 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).<sup>3</sup> 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

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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).

<sup>3</sup>Using firm-level data from Portugal, Martins (2019) shows that shop-floor employee representation fosters investments in training and firm productivity and has limited effects on wages, given the predominance of sectoral collective agreements.

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) take into explicit account forms of shop-floor ER, such as work councils, and find that establishments with ER do not have lower investments than those without it. Recently, Jäger et al. (2020) 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 the years to come, the understanding of the institutional forces driving their adoption and mediating their consequences is still insufficient. In this paper we make some steps in filling this gap.

The remaining of the paper is organized as follows. Section 2 discusses the theoretical channels through which ER may affect the use of advanced technologies. Section 3 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 4 investigates the causal effect of ER on technology adoption through an RDD design based on Italian data. Section 5 concludes.

## 2 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 via either hold-up or insider protection. In the hold-up view industrial relations are seen as informed by the strategic opportunism of unions, which seek to exploit their bargaining position to benefit employees. In the absence of binding employment contracts, institutions that give control rights to workers strengthen the worker 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* appropri-

ated by labor. As a result, 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.

When considering specific technologies such as robots and advanced digital tools, a similar prediction can be obtained by considering the role of ER in relation to firm-level decisions regarding technological restructuring. As argued by Genz et al. (2019), in fact, the presence of ER bodies allows employees to exert greater control rights over a wide range of organizational changes taking place at the workplace, including the introduction of new technologies. In most contexts employee representatives have the rights to be informed and consulted on issues related to job displacements, work safety and employee supervision and monitoring that involve 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. In principle, even though employers are considering the possibility to use these technologies, the process of adoption might consume considerably longer time in presence of ER compared to the cases where ER is absent and thus discourage investment in the first place. Hence, one of the indirect ways in which ER may discourage the use of these technologies is by imposing delay costs, impeding firms to respond to profitable market opportunities in a timely manner (Freeman and Lazear, 1995).

**Monopoly power, labor conflict, and insider protection.** Opposite predictions, however, can be obtained by considering a set of institutional frictions that can be associated with the presence of ER. The most direct one is related to the fact that representation institutions can push wages above the competitive level. In the standard competitive model, the impact of a wage increase on the demand for labor and capital can be divided into two effects (see, e.g., Booth (1995)). First, there is a substitution effect as higher wages reduce the relative price of capital and provide incentives to replace labor by machines. Second, there is a scale effect as less output is produced after the wage increase. Under certain conditions, i.e. if the substitution effect dominates the scale effect, ER may induce firms to adopt automated capital at a faster rate as a way to substitute away costly labor (Denny and Nickell, 1991).<sup>4</sup>

A similar prediction can be derived considering the effect of ER on labor contracts. On this respect, a recent work by Fornino and Manera (2021) suggests that flexibility represents the distinctive comparative advantage of labor, which makes it better suited than automated

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<sup>4</sup>Along these lines, Acemoglu and Restrepo (2021) report country-level evidence showing that greater unionization rates are associated with higher robots adoption, with the effect being presumably driven by the fact that unions rise labor costs.



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, e.g., Heery, 2004; Salvatori, 2012; Visser, 2002) such advantage disappears, allowing factor substitution to proceed faster. As a result, we should expect the presence ER to be associated with positive investments in robots and advanced digital tools and possibly higher labor displacement, especially in contexts where employment protection legislation is the strictest.<sup>5</sup>

Finally, ER can affect technology adoption through the interplay between institutionalized labor conflict and job design. A long tradition of research argues that, in presence of conflicting interests over effort provision, technological choices should be interpreted as responses to given power relations, and not only economic convenience (Gintis, 1976; Marglin, 1974; Bowles, 1985; Skillman, 1988; Duda and Fehr, 1987; Pagano, 1991). In our context, this approach would suggest that, whenever ER bodies are combined with highly conflicting industrial relations, the use of robots and other advanced digital tools will rise. The latter may indeed be part of employers' strategic response aimed at disorganizing labor and restoring their bargaining position.<sup>6</sup> More recently, Presidente (2020) addresses the role of labor conflict in relation to technology adoption. In particular, he documents a positive association between lagged measures of strike activity and robot adoption at the industry-country level. He argues that labor-friendly institutions induce investment in industrial robots, particularly in sunk-cost intensive industries, where higher vulnerability to hold-up strengthen workers' bargaining power. Obviously, such 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 as discussed above.

A common assumption in all these arguments is that advanced technologies are labor-saving, i.e. new technology and workers are substitutes in the production process. The validity of these positions is thus dependent on the elasticity of substitution between labor and automated capital (Sachs and Kotlikoff, 2012; Berg et al., 2018; Sachs et al., 2015; Nordhaus, 2015).<sup>7</sup>

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<sup>5</sup>Notice, however, that whether unions oppose flexible employment is controversial. Recent research has showed that unions may favor the employment of a buffer of temporary workers, if this is functional to absorb variations in the labor input use thereby protecting permanent, core workers (Devicienti et al., 2018). ER has been found to increase flexibility also along other margins, such as working-time arrangements (Burdin and Pérotin, 2019).

<sup>6</sup>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 labor. 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 evidence supporting a reverse causal relationship: labor-saving technologies caused social unrest in 1830s England.

<sup>7</sup>Clearly, labor and capital inputs may show different degrees of substitutability across different types of technologies, with industrial robots competing more directly with middle-skilled workers in manufacturing and in

Taken together, this strand of literature would predict that, as long as advanced technologies are sufficiently close substitute of human labor, ER leads to higher rate of adoption to the extent it creates frictions (i.e. higher wages, less flexible employment contracts, more conflicting employment relations) which rise incentives to replace workers with automated capital.

**Complementarity between technology and work organization.** Finally, ER may affect technology adoption via its direct effect on work organization. This is especially relevant in presence of organizational complementarities, i.e. situations in which distinct organizational practices exert an influence on the profitability of the others, which may explain potential clusters of practices and technological choices (Brynjolfsson and Milgrom, 2012). In this framework, ER can foster organizational systems and practices that are complementary to advanced technologies in three main respects. First, ER favors the internal transmission of information in a way that complements information processing based on automated capital such as robots and other advanced digital tools, with potentially positive effect on the reorganization of production processes (see, e.g., Wu et al. 2019, 2020).<sup>8</sup> 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 others, 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). Secondly, several contributions document that unionization is often associated with higher investment in training. This can be explained by the fact that unions have strong preferences toward gains in competitiveness through productivity compared to labor costs (Martins, 2019). Also, training can be incentivized by more compressed wage distributions in unionized firms compared to non-unionized ones (Dustmann and Schönberg, 2009). In either cases, alongside an effect that is potentially channeled through wages, the higher frequency of training in firms with ER implies they may be more accustomed than firms without ER to bear some of the fixed costs (e.g organization of training sessions) associated with the acquisition of new skills that are complementary to advanced technologies and they

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larger firms (Zolas et al., 2020), and other advanced digital tools such as data analytics being mostly adopted as a key ingredient at the management level of several business functions, such as electronic commerce, supply chain management, customer relations and marketing, and human resources (Dixon et al., 2020).

<sup>8</sup>On this respect, Wu et al. (2019) show that data analytics technologies play an important role in strengthening firm’s search capabilities for acquiring diverse knowledge from many different sources.

can thus be more inclined toward their adoption. Thirdly, workplace governance systems based on ER can be complementary to rich job designs, reducing workers’ exposure to job automation risk and enabling greater labor-technology complementarity (Belloc et al., 2022). This may in turn favor the selection of efficiency-enhancing robots and advanced digital tools, which at the same time improve working conditions.<sup>9</sup> 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 effects suggest that, in the presence of ER, high adoption rates of robots and advanced digital tools can go together with relatively cooperative industrial relations that promote processes of organizational restructuring.

**Summary.** To sum up, we identify three main mechanisms through which ER can affect investments in advanced technologies: hold-up /insider protection, institutional frictions, and work organization. While the former 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 other features of the employment relationship such as labor market regulation, task composition, and the 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.

### 3 Evidence from EU workplaces

#### 3.1 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 2019 (van Houten and Russo, 2020). ECS data cover a representative sample of non-agricultural establishments employing at least 10 employees and located in all EU countries.<sup>10</sup> A crucial advantage of this survey is that it provides harmonized cross-country information on employee representation and use of advanced technologies. In addition, the survey reports rich details about management practices and organizational design at the workplace level.

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<sup>9</sup>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.

<sup>10</sup>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.

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

*B. 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 the interaction with people”. As a validation exercise, Figure 1 plots the correlation between our measure of robot usage and the number of industrial robots (units per 10000 employees) as reported by the International Federation of Robotics (IFR). Both measures are positively correlated. This is reassuring, considering that IFR data on robot density has been extensively used in the literature. In addition, we analyze the association between the presence of ER and the utilization of advanced digital tools such as data analytics, i.e. 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 to 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 variable as a general index of advanced digitalization at the establishment.

*C. Other variables.* Finally, managers report information on whether the establishment is part of a multi-site firm, establishment size and age, workforce composition (fraction of part-time 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 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%).<sup>11</sup> 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, 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 shirking establishments.

### 3.2 Correlation between ER and the use of advanced technologies

We begin by considering the following baseline regression model:

$$Y_{ijc} = \beta_0 + \beta_1 \text{ER}_{ijc} + \mathbf{b}\mathbf{X}_{ijc} + \varepsilon_{ijc} \quad (1)$$

where subscripts  $i$ ,  $j$  and  $c$  denote the establishment, industry and country, respectively;  $Y_{ijc}$  is a dummy variable equal to 1 if the establishment  $i$  in industry  $j$  and located in country  $c$  uses advanced technologies, either robots or other advanced digital tools;  $\text{ER}_{ijc}$  is a dummy variable for the presence of ER at the establishment level;  $\mathbf{X}_{ijc}$  is the vector of controls;  $\varepsilon_{ijc}$  are the residuals. Despite the availability of a rich set of potential control variables, we prefer a parsimonious specification in order to avoid including factors that may also be affected by the presence of ER.

In columns (1)-(5) of Table 2, we report the results from estimating a series of Linear Probability Models where the dependent variable is the use of robots. In column (1), we estimate a model in which we only include a dummy variable that takes value one for establishments in which there is an ER body in place and a full set of industry and country dummies. The presence of ER is positively associated with the probability of using robots. In columns (2)-(5), we sequentially add more controls to see the robustness of the results. In column (2),

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<sup>11</sup>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. (2019) 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, Zolas et al. (2020) 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 less than 10 workers.

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 one for establishments subject 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 additionally control 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 1.4 percentage point increase in robot usage. Finally, in columns (6)-(10), we repeat the same exercise and sequentially add 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.<sup>12</sup>

In Table A.1.1, we report additional estimates in which the ER dummy variable is unpacked into multiple categories, i.e. 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 with advanced digital tools.<sup>13</sup>

### 3.3 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 in Section 2. 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 and insider protection frameworks posit that unionized firms may reduce investments in advanced technologies either to prevent ex-post quasi-rent extraction by workers or to avoid time consuming negotiations. In both cases one should expect

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<sup>12</sup>We obtain qualitatively similar estimates when average marginal effects are obtained from Probit models. Results are available upon request.

<sup>13</sup>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.

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. On this respect, notice that an implicit assumption behind the hold-up mechanism is that automation-related investments can be assimilated to any other form of capital inputs and are thus vulnerable to similar hold-up problems. This, however, may not be the case. In the standard hold-up story if employers buy machines with firm-specific features, ex-post they can be threatened by workers who refuse to operate the machines (knowing they have zero reselling value) unless the employers raise their wages. Anticipating this, the employers may decide not to invest. Yet, if advanced technologies such as robots can operate by themselves, or at least by involving a much smaller number of employees, the ex-post rent extraction strategy of the workers would be less credible. As a result the discouraging effect of ER with respect to technology adoption would be much weaker (if not absent).

**Labor 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 labor-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 labor-management relations. To check for this, we estimate equation (1) while controlling for the occurrence of industrial actions in the last three years (strikes, work-to-rule, or manifestations). Strike threats are an important tool to achieve higher wages and protect insiders (Booth, 1995).<sup>14</sup> 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, 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 labor-management conflict.

Second, we test whether ER induces greater technology adoption by increasing labor rigidity and hence eliminating the main comparative advantage of labor vis-à-vis automated capital (Fornino and Manera, 2021). Managers report whether employee representatives directly influenced management decisions on a wide range of areas including dismissals. Indeed, ER structures are granted with special prerogatives in relation to dismissals in some European countries<sup>15</sup> and this may restrict the ability of employers to adjust labor. Alongside information on the strength

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<sup>14</sup>Unfortunately, we cannot distinguish between different types of industrial actions, which in turn may have different effects on capital investments (Moene, 1988).

<sup>15</sup>For example, companies are usually required to inform and consult employee representatives in case of collective redundancies.

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 one 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 small 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.<sup>16</sup>

Third, we look at how ER may affect the adoption of advanced technologies via increasing labor 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 employee representation in raising wages could be rather limited. First, estimates reported in columns (5) and (6) of Table 3 include a dummy variable equal to one for establishments reporting a reduction in employment in the last three years and its interaction with the presence of ER. Although this is a very crude approximation, one would expect, following the logic of the capital-labor substitution channel, greater use of advanced technologies in establishment with ER that reduced employment compared to establishments without ER. We find, however, that shrinking establishments are less likely to

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<sup>16</sup>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 exist some complementarity between EPL and ER (e.g. ER may act as shop-floor rule enforcement mechanism of EPL), 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 in Appendix). Contrary to the employment rigidity argument, we find that the effect of ER on robot usage is only present 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.



report the use of robots regardless of whether an ER body is present or not (no significant effect for other advanced digital tools).<sup>17</sup> In addition, we exploit specific features of European labor market institutions characterized by the coexistence of workplace employee representation and centralized wage-setting systems. One could argue that in more centralized wage settings plant-level wages 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 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).<sup>18</sup> 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 show that the positive effect of ER on robot and other advanced digital tools is restricted to workplaces operating in high wage centralization environments, i.e. settings in which one would expect a more limited influence of workplace ER on wages.

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.<sup>19</sup> Results from this exercise are presented in columns (1)-(4) of Table A.1.4 for robot 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 only holds for the subsample of establishments located in rapidly-ageing countries. This suggests that ER facilitates major reorganization of the production process and fosters the use of robots particularly in environments where there is scarcity of middle-age workers.

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

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<sup>17</sup>As long as production efficiency rises sufficiently after adoption, expanding employment could still be consistent with a process of capital-labor substitution driven by high wages. Therefore this evidence should be taken with caution.

<sup>18</sup>Evidence on weaker wage effects of works council in workplaces covered by collective agreements is somewhat mixed (Jirjahn, 2017). Recent studies on shop-floor employee representation in Portugal and German codetermination show no effects on wages (Martins, 2019; Jäger et al., 2020).

<sup>19</sup>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.

**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 significantly differ from establishments where ER is absent. If any, 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.<sup>20</sup> 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.<sup>21</sup>

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 analyze this aspect we run Equation (1) including alternatively: two dummy variables which equal one when managers and employees meet, respectively, on a regular and irregular basis to discuss about work organization (being “no meetings” the benchmark category) and their interaction with ER; and two dummy variables which equal one when managers use practices of information dissemination (e.g. newsletter, website, notice board), respectively, on a regular and irregular basis (being “no dissemination” the benchmark category) and their interaction

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<sup>20</sup>Notice, however, that the effect of ER on robots is negative when no decision on work organization was made.

<sup>21</sup>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 favors 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 harm movements. We then regress the use of robot and advanced digital tools against ER in sub-samples characterized by a relatively high/low incidence of bad tasks (see Table A.1.5 in the 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 favoring the adoption of robots explicitly targeted 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.

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

## 4 Identification through size-contingent legislation: evidence from Italian firms

### 4.1 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 at 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 a regression discontinuity design (RDD) that exploits size-contingent regulations governing the establishment of ER in Italy.<sup>22</sup>

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 at the workplace thorough the creation of democratically elected bodies called “Rappresentanze Sindacali Aziendali” (RSA). The latter can be established upon 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 employee representation rights.<sup>23</sup> Originally,

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<sup>22</sup>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 adequate account 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 Appendix 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.

<sup>23</sup>Article 35 limits the application of Article 19 to production units with more than 15 employees, where by production units is meant headquarters, establishments, branches, offices or independent departments. Later, the jurisprudence has extended such 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.

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, 2/3 of the representatives are elected by all the employees and the remaining 1/3 is designated or elected by union members).

Both RSA and RSU are granted a series of rights to adequately perform their function. The Workers’ Statute (Articles 20-27) recognizes to 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 directly pertaining to the organization of work, including working hours, workloads, vocational training, and the split of productivity increases between firms and workers.<sup>24</sup> 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 which needs to be considered is that, alongside ER bodies, there are other labor market institutions that change discontinuously at the threshold of 15 employees. Two in particular are the most relevant. First, 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 the Italian law such scheme can be used only by firms above the 15-employees threshold.<sup>25</sup> 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

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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.

<sup>24</sup>The logic inspiring the Italian system of two-tier collective bargaining is similar to the one of mixed-systems that are 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, 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.

<sup>25</sup>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.

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 considerably attenuated by recent legislative changes, in particular the so-called Fornero Law and the Jobs Act. The former, passed in 2012, has considerably restricted 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 of 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).

## 4.2 RIL-INAPP survey: panel of Italian firms

The institutional setting described in the preceding section 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 13000 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 one if an RSU or an RSA is established in the company. Investments in automation technologies are measured by means of three different dummy variables. The first one is equal 1 if the firm, over the 2015-2017 period, has undertaken investments in robots. The second one is equal 1 if the firm, over the 2015-2017 period, has undertaken investments in other advanced digital tools such as big data analytics, Internet of things, virtual reality and cybersecurity. The third one is equal 1 if the firm, over the 2015-2017 period, has undertaken investments in more conventional ICT

assets, including computer and hardware to automatize 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.

### 4.3 RD 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 following model:

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

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

Conventional continuous-based inference methods for RDD rely on nonparametric 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,<sup>26</sup> we rely on the alternative local randomization approach to RD, which stipulates that treatment assignment may be approximated by a local random experiment near the cutoff  $c$  (Lee, 2008; Cattaneo et al., 2015, 2016).<sup>27</sup>

The most important step is to select the window around the size cutoff 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 nonstandard 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. In Table A.2.1, we report the results of the window selection

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<sup>26</sup>We count 13148 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 RD 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).

<sup>27</sup>For practical implementation, we use the functions *rdwinselect* and *rdrandinf*, part of the the *rdlocrand* package developed by Cattaneo et al. (2015).

procedure, including randomization-based p-values from balance tests and the covariate with minimum p-value for different windows. We analyze all symmetric windows around the cutoff 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 Appendix 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 cutoff. Figure 6 shows clear evidence of a first-stage effects with a discontinuity in the presence of ER at the cutoff point.<sup>28</sup> 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 cutoff is more than double the control group. The null hypothesis of no treatment effect is strongly rejected with p-value of 0.000.

Having documented that there is a discontinuity in the incidence of ER around the cutoff, we now turn to our outcomes of interest, i.e. investments in robots and digitalization. Visual inspection from 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, i.e. 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 advance digital tools in the last two years between treatment and control units. This effect is equivalent to a 12% of one standard deviation of the share of firms investing in advance 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 of 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 control firms. Null effects are also rejected in this case (p-value of 0.081). Given the presence of imperfect compliance,

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<sup>28</sup>The figure 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.

these estimates represent intention-to-treat (ITT) effects.

**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 innovations. In column (1), we report a significantly positive effect of ER on the training rate (3.5 p.p.) around the cutoff, i.e. 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 innovations, we find a increase of roughly 6 p.p. in the likelihood of process innovations. This is equivalent to a 20% increase in process innovations 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 2, 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 labor costs and induces factor price distortions and allocation inefficiencies, one should observe that the greater use of advanced technologies results in layoffs, particularly among production and 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 employee representation 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 RD design. First, we check for systematic differences in terms of covariates between units below and above the cutoff. 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  $[-5, 5]$ . Results are reported in Table A.2.2 and Figure A.2.1 in Appendix. Reassuringly, we do not find evidence of treatment effects for any of these characteristics. Second, we analyze the density of the forcing variable within our selected window  $[-5, 5]$ , i.e. whether the number of establishments just above the cutoff is similar to the number of establishments just below the cutoff. Sorting around the cutoff may occur if firms manipulate their size in order to block employees’ attempts to trigger ER rights. The number of control firms immediately below the cutoff (1242) and treatment firms above the cutoff (1170) is slightly unbalanced. However, a binomial test that the probability of being treated is 0.5 does not reject the null ( $p\text{-value}=0.148$ ), indicating no evidence of sorting around the cutoff in the chosen window (Cattaneo et al., 2017).

Third, we consider the sensitivity of the results to our window choice. We replicate the local-randomization analysis for both smaller and larger windows 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 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 in 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 is not surprising considering that robot usage is highly concentrated among larger firms and our baseline RD analysis is restricted to relatively small firms.

Finally, we consider placebo cutoff values at which the probability of treatment should not change. We expect not to find any effect at these “fake” cutoffs. To circumvent mis-specification problems, estimates only include 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 cutoff 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 in Appendix).

**Additional robustness checks: fuzzy RDD, donut-hole and linear adjustment.**

First, as mentioned in Section 4.1, the firm size threshold of 15 employees does not perfectly

determine 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 A of Table 11 we also report estimates from a Fuzzy RDD using as an instrument for ER status the 15 employees threshold. Results point in the same direction as our baseline RDD estimates. In this case, effects are larger but their interpretation is different: they represent the causal effect of ER only for those firms on the margin for which the presence of ER bodies is affected by the size threshold (i.e. the average treatment effect on the compliers).

Second, 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).<sup>29</sup> For this reason, in panel B of Table 11, we report estimates from a donut-hole specification in which we exclude firms with 14, 15 or 16 employees. This donut approach also account for sorting around the cutoff. 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 cutoff. 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. Finally, we also estimate the 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 a untransformed (constant) model. Our baseline results for advance 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 cutoff, 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 in Section 4.2, two other important labor 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 firm’s technological choices. We tackle this issue in several ways. First, in rela-

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<sup>29</sup>In the Italian labor Law, the 15-employee threshold is calculated on a full-time equivalent basis, with part-time workers counted in proportion to the number worked hours and temporary staff according to the average number of months worked in previous years.

tion to employment protection, it is worth noting that recent labor 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 (2015-2018) in which both reforms, i.e. Fornero Law (2012) and the Jobs Act (2014), had already been implemented.<sup>30</sup> No other major regulatory changes affecting firms below and above the 15 employees cutoff differently occurred during the period under consideration.<sup>31</sup> Moreover, 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 to use 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 plausibly assume that firing restrictions were particularly binding for this group of firms before 2015.<sup>32</sup> Results are remarkably similar, suggesting that other regulations are not driving our main results (see Appendix Table A.2.5).<sup>33</sup>

## 5 Conclusions

Our study shed light on the interplay between labor institutions and the use of advanced technologies at the workplace. We found no evidence that employee representation discourages technology adoption. Using establishment-level data from 26 European countries, we document a positive correlation between shop-floor employee representation 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 does seem to be driven neither by adversarial labor-management relationships, nor by ER-induced labor rigidity. ER seems to favor certain work systems and practices, such as training, working time management and information sharing, that are complementary to the adoption of new technologies.

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<sup>30</sup>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 fully captured in the 2015 RIL wave.

<sup>31</sup>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.

<sup>32</sup>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 to use CIG (2% in the whole sample).

<sup>33</sup>One could further investigate the potential confounding effect of labor market reforms on technology adoption by following a Difference in Regression Discontinuities design. Using this approach and the 2010-2015 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 fully rely on this approach as information on most advanced technologies is only available for the 2018 RIL wave. We can only implement a diff-in-disc design for ICT investments ( “Dotazioni informatiche: computer, hardware per automazione e digitalizzazione dei processi produttivi”) as information was collected on a consistent manner over the period 2007-2018, i.e. before and after the reform. Our estimates (available upon request) do not suggest a differential increase in ICT investments in the post reform period for firms above the 15 employees threshold.

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 rises the acquisition of advanced digital tools significantly. We also found an increase in the training rate and greater incidence of process innovation with no employment effects around the cutoff. Taken together, these results suggest that granting institutionalized channels of employee voice on average may favor, and at a minimum does not harm, the adoption of advanced technologies at the workplace.

The documented effect of ER on advanced technologies may be consistent with a conventional capital-labor substitution mechanism, as greater workers' bargaining power may result in higher labor 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 only present 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 shows no indication of major changes in both the level and composition of employment around the cutoff as the labor cost channel would predict.

A limitation of our regression discontinuity design relates to the lack of time variation in policy rules regulating Italian ER bodies. This makes our strategy vulnerable to potential measurement errors in the running variable and the existence of other policy discontinuities hitting Italian firms at 15 employee cutoff, such as employment protection legislation and short-time work schemes. The extensive battery of validation and robustness checks provided in the paper mitigate yet does not eliminate these concerns.

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 US (?) than in European countries (?Hirvonen et al., 2021; Aghion et al., 2021). These differences may be attributed to labor market institutions, particularly in relation to the incidence of worker voice arrangements. Indeed, our paper suggests that workplace employee representation 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 favor 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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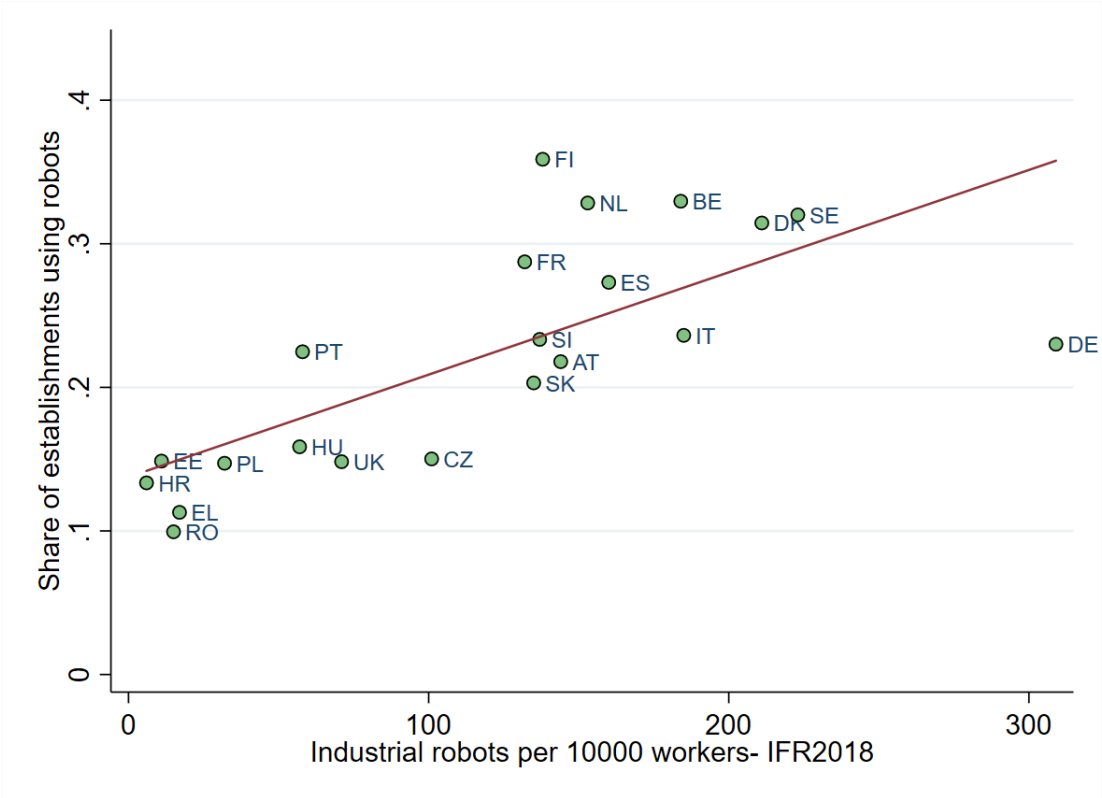
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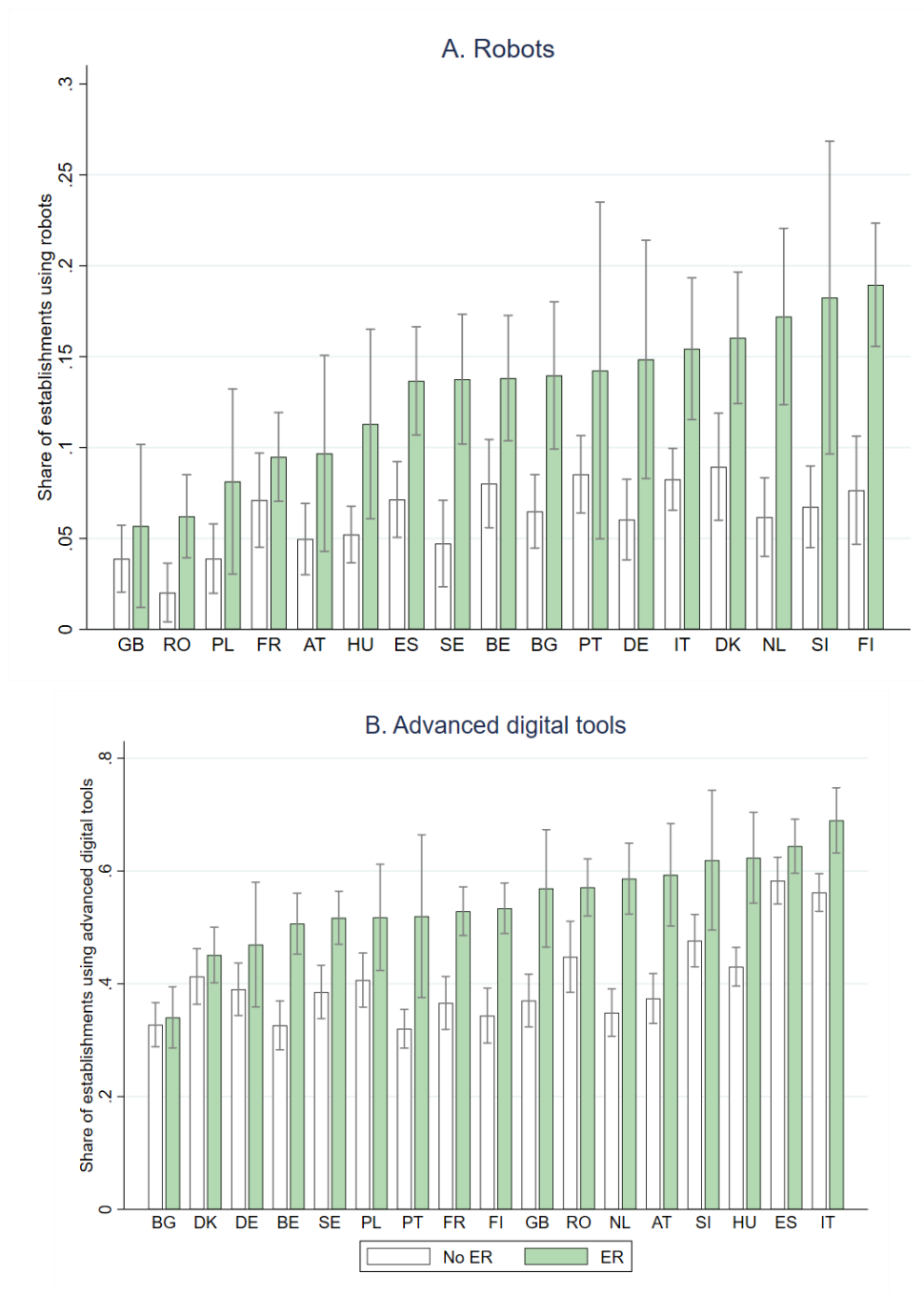
# Figures and Tables

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



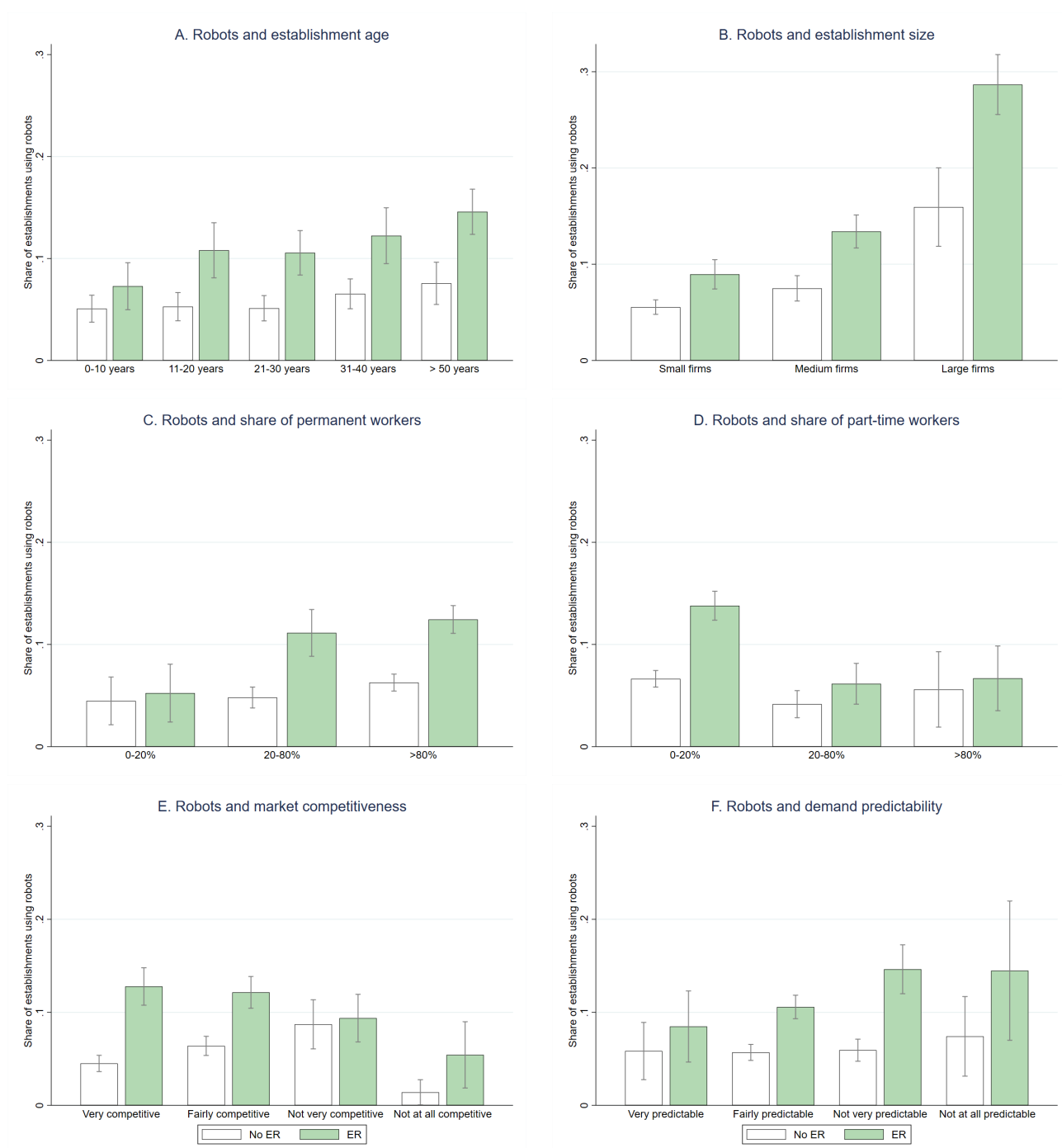
Notes: Pooled data from the European Company Survey 2019. Robot usage refers to establishments using “programmable machines that are capable of carrying out a complex series of actions automatically”. Robot density is the number of industrial robots per 10000 workers (source: International Federation of Robotics 2018).

Figure 2: Robot and other advanced digital tools usage by workplace ER status in selected countries.



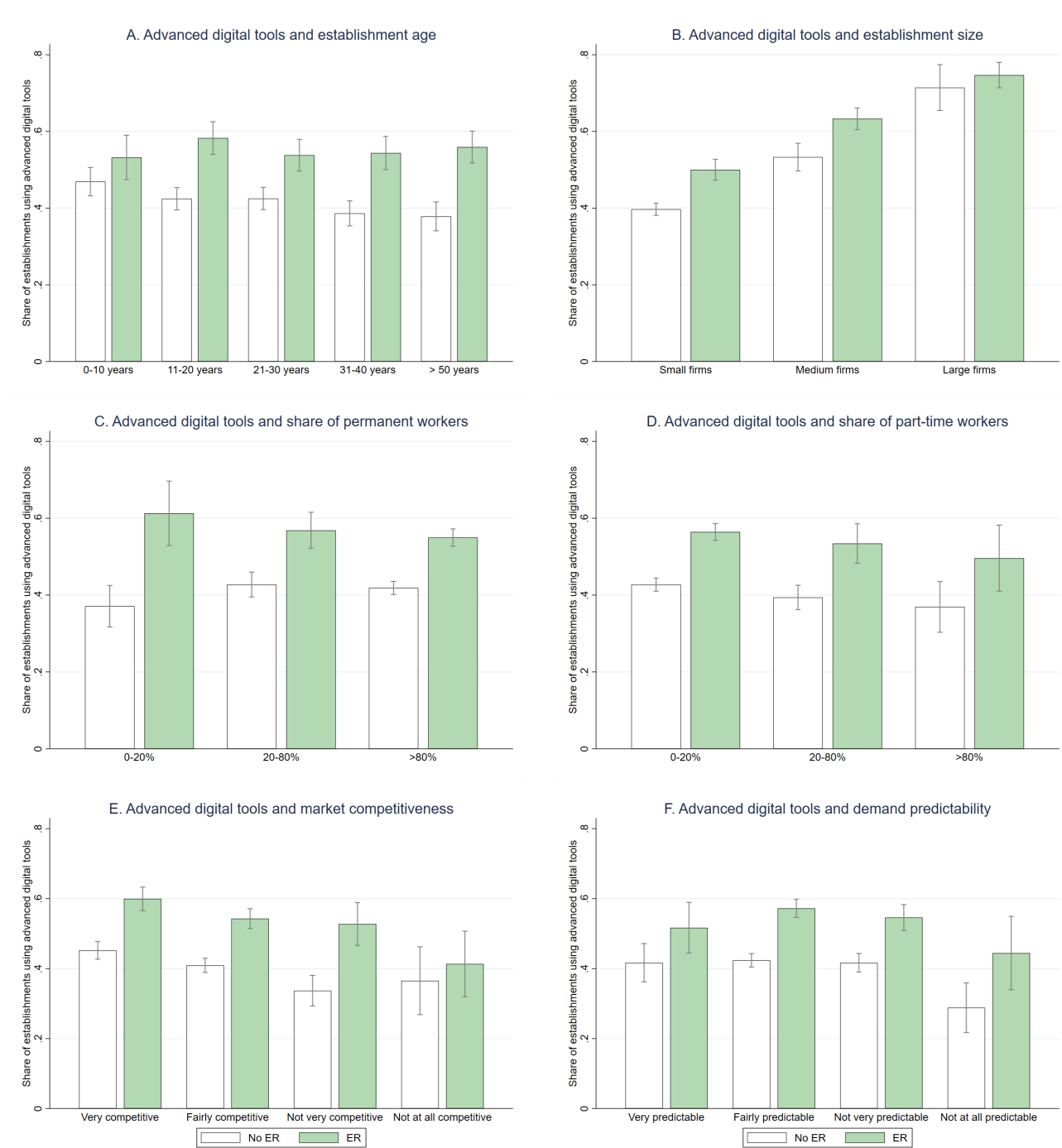
Notes: Pooled data from the European Company Survey 2019 (selected countries). Sample weights are used. The use of robots refers to establishments using “programmable machines that are capable of carrying out a complex series of actions automatically”. Advanced digital tools refers to establishments using “digital tools for analysing data collected at this establishment or from other source” to improve the processes of production or service delivery.

Figure 3: Robots and establishment characteristics.



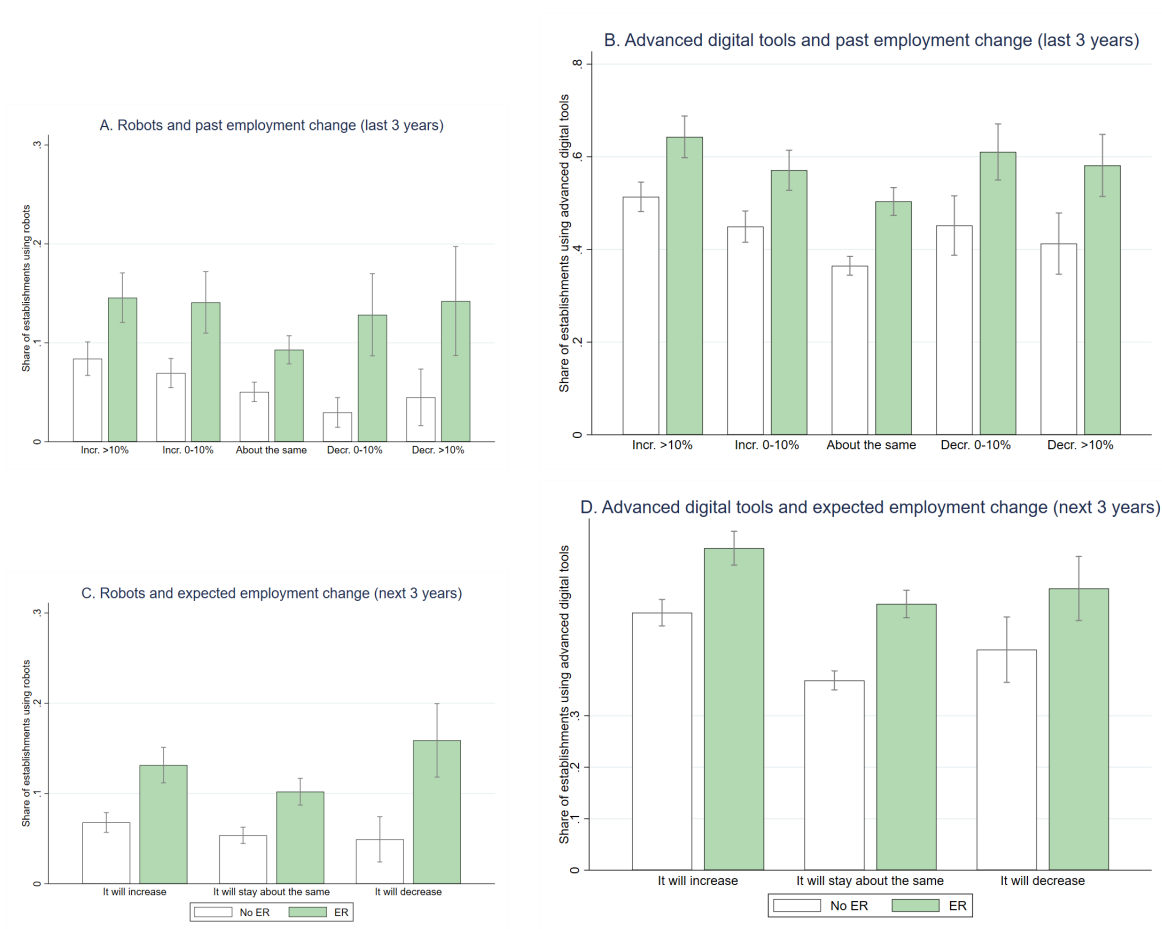
Notes: Pooled data from the European Company Survey 2019. Sample weights are used. Robots refer to establishments using “programmable machines that are capable of carrying out a complex series of actions automatically”.

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.

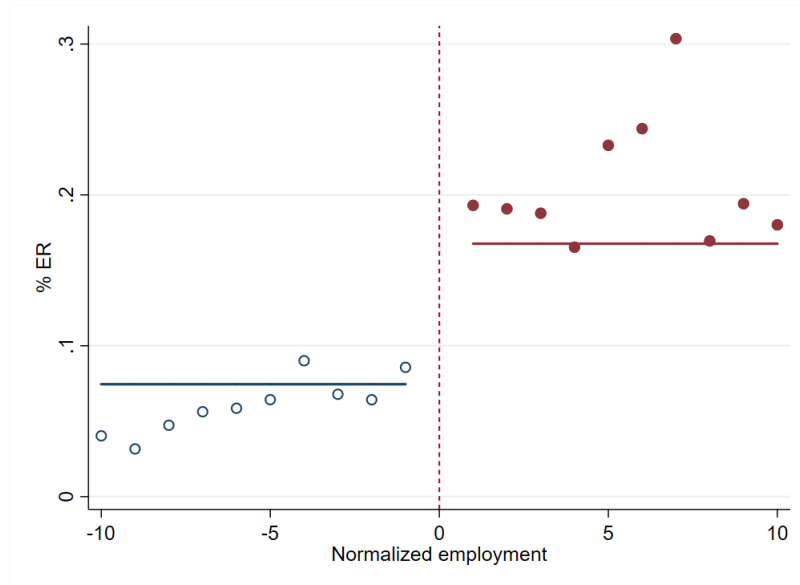
Figure 5: Robots and advanced digital tools by employment change status.



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”.

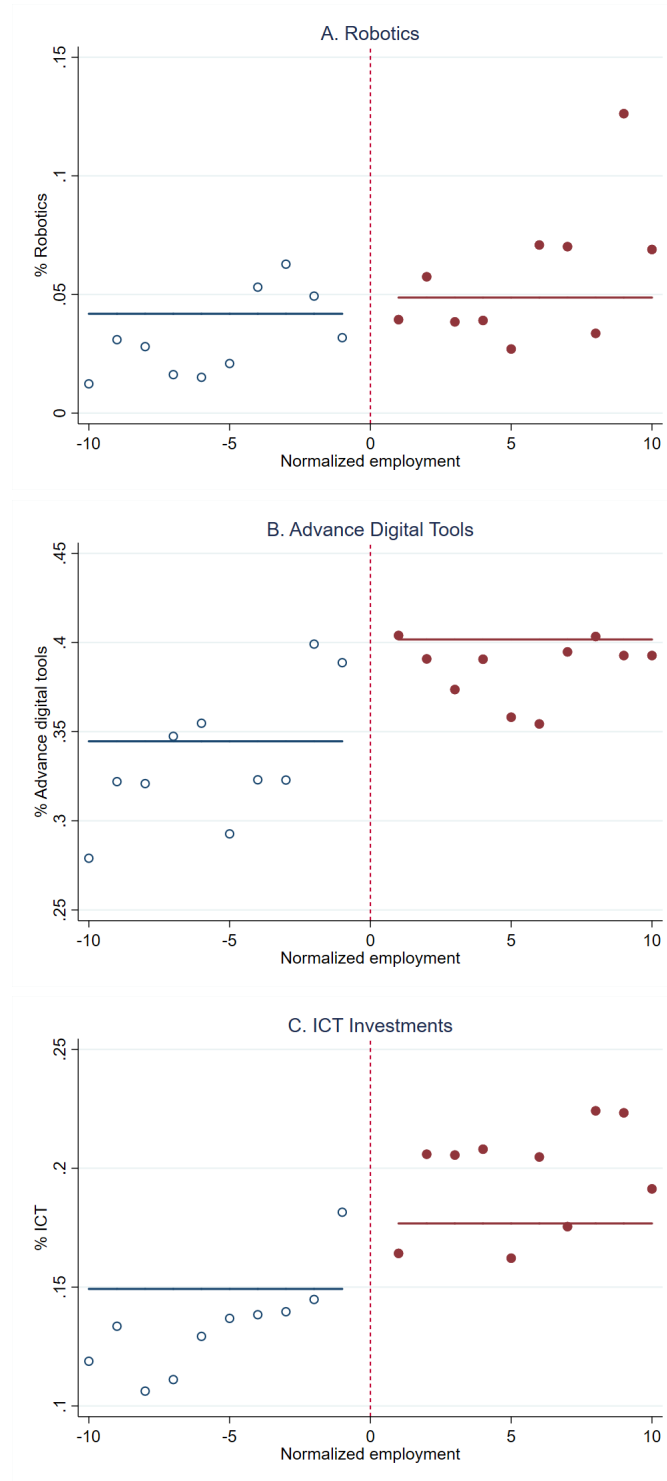


Figure 6: RD plot: incidence of employee representation (ER)



Notes: *rdplots* of the incidence of employee representation using 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. RD-plots restricted to the window  $[-10, 10]$  with polynomial degree = 0 and a uniform kernel.

Figure 7: RD plots: investment in automation technologies and digitalization



Notes: *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. Rdplots restricted to the window  $[-10, 10]$  with polynomial degree = 0 and a uniform kernel.

Table 1: Main variables' description and descriptive statistics

VARIABLES	DESCRIPTION AS IN THE ECS QUESTIONNAIRE	MEAN	STD.DEV.
ER	An official employee representation currently exists in the establishment (yes/no)	0.247	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 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-resource manager, personnel manager (yes/no)	0.184	0.388
Manager position: training	Position held by the manager: training manager (yes/no)	0.003	0.058
Manager position: finance	Position held by the manager: finance/accounting manager (yes/no)	0.170	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.

Table 2: Robots, advanced digital tools and ER.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Robots					Advanced digital tools				
ER	0.070*** (0.005)	0.016*** (0.005)	0.014*** (0.005)	0.015*** (0.006)	0.014** (0.006)	0.150*** (0.008)	0.042*** (0.008)	0.041*** (0.008)	0.043*** (0.008)	0.038*** (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 LPM models with robust standard errors in parentheses. In columns (1)-(5), the dependent variable is a dummy variable indicating whether the establishment uses robots, i.e. programmable machines that are capable of carrying out a complex series of actions automatically. In 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. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

Table 3: Robots, advanced digital tools and ER: institutional frictions.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	Adversarial relations		Labour rigidity		Capital-labour substitution	
	Robots	Adv. digital tools	Robots	Adv. digital tools	Robots	Adv. digital tools
ER	0.014** (0.006)	0.039*** (0.008)			0.014** (0.006)	0.036*** (0.009)
Strike	0.021 (0.025)	0.049 (0.045)				
ER × Strike	-0.002 (0.034)	-0.077 (0.052)				
ER influence on layoffs: no decisions made			0.001 (0.009)	0.040*** (0.013)		
ER influence on layoffs: not at all/small extent			0.017** (0.007)	0.030*** (0.010)		
ER influence on layoffs: moderate / great extent			0.028** (0.011)	0.061*** (0.014)		
Reduced employment					-0.019*** (0.007)	-0.013 (0.013)
ER × Reduced employment					0.005 (0.013)	0.015 (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 LPM 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, work-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 take 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.\*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

Table 4: Robots, advanced digital tools and ER: influence on training and work organization.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	Robots			Advanced digital tools		
ER influence on training: no decisions were made	-0.009 (0.012)			0.011 (0.017)		
ER influence on training: not at all/to a small extent	0.009 (0.007)			0.013 (0.010)		
ER influence on training: to a moderate or great extent	0.029*** (0.008)			0.080*** (0.011)		
ER influence on organization: no decisions were made		-0.023** (0.011)			0.002 (0.018)	
ER influence on organization: not at all/to a small extent		0.016** (0.007)			0.008 (0.010)	
ER influence on organization: to a moderate or great extent		0.024*** (0.007)			0.084*** (0.011)	
ER influence on working time: no decisions were made			-0.011 (0.010)			0.013 (0.015)
ER influence on working time: not at all/to a small extent			0.005 (0.007)			0.012 (0.010)
ER influence on working time: to a moderate or great extent			0.039*** (0.008)			0.084*** (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 LPM models with robust standard errors in parentheses. In columns (1)-(3) the dependent variable is a dummy variable indicating whether the establishment uses robots, i.e. programmable machines that are capable of carrying out a complex series of actions automatically. 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.\*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

Table 5: Robots, advanced digital tools and ER: practices of employee involvement.

VARIABLES	(1)	(2)	(3)	(4)
	Robots		Advanced digital tools	
ER	0.021 (0.022)	0.000 (0.011)	0.025 (0.032)	0.015 (0.017)
Regular-basis meetings between employees and manager	0.030*** (0.010)		0.215*** (0.017)	
ER × Regular-basis meetings between employees and manager	0.004 (0.023)		0.004 (0.033)	
Irregular-basis meetings between employees and manager	0.026*** (0.010)		0.105*** (0.017)	
ER × Irregular-basis meetings between employees and manager	-0.029 (0.024)		0.031 (0.034)	
Regular-basis information dissemination		0.014** (0.006)		0.195*** (0.010)
ER × Regular-basis information dissemination		0.025* (0.013)		0.011 (0.019)
Irregular-basis information dissemination		-0.009 (0.006)		0.084*** (0.011)
ER × Irregular-basis information dissemination		-0.000 (0.014)		0.028 (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 LPM models with robust standard errors in parentheses. In columns (1)-(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)-(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.\*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

Table 6: Main variables' description and descriptive statistics of the RIL-INAPP panel sample.

VARIABLES	DESCRIPTION AS IN THE RIL-INAPP QUESTIONNAIRE	MEAN	STD.DEV.
ER	RSA or RSU is currently exists 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
Nonstandard contracts	Share of employees with nonstandard contracts (e.g. fixed term, agency, work-on-call)	0.158	0.201
Workers w/tertiary edu.	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, 2015-2017.



Table 7: Randomization-based approach: main results (RIL-INAPP panel of Italian firms).

	(1)	(2)	(3)	(4)
	ER	Robots	Advance digital tools	ICT Investments
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	1,157	1,170	1,170	1,154
Sample size control	1,221	1,242	1,242	1,233

Notes: Results from the RDD estimates using a local randomization approach with an analysis window of [5,5] around the cutoff and based on RIL-INAPP panel of Italian firms (local-constant polynomial approximation using a uniform kernel). CI denotes 95% confidence intervals. 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 Internet of things, big data analytics, virtual reality and cybersecurity. In column (4), the outcome variable 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 nonstandard 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 Calonico et al. (2016).

Table 8: Other outcomes: training and innovation (RIL-INAPP panel of Italian firms).

	(1)	(2)	(3)
	Training rate	Process innovation	Product innovation
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	1,030	1,170	1,170
Sample size control	1,114	1,242	1,242

Notes: Results from the RDD estimates using a local randomization approach with an analysis window of [5,5] around the cutoff (local-constant polynomial approximation using a uniform kernel). CI denotes 95% confidence intervals. 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 nonstandard 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 Calonico et al. (2016).

Table 9: Employment outcomes (RIL-INAPP panel of Italian firms).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Employment growth 2017-2018	Employment growth 2015-2018	Hiring rate	Separation rate	Quit rate	Layoff rate	Vacancy rate
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	1,060	1,060	1,049	1,052	1,059	1,058	1,060
Sample size control	1,116	1,116	1,101	1,104	1,116	1,114	1,116

Notes: Results from the RDD estimates using a local randomization approach with an analysis window of [5,5] around the cutoff (local-constant polynomial approximation using a uniform kernel). Outcome variables: (1) log change in employment (period 2017-2018); (2) log change in employment (period 2015-2018); (3) hiring rate 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 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 nonstandard 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 Calonico et al. (2016).

Table 10: Workforce composition (RIL-INAPP panel of Italian firms).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Production worker share	Clerical worker share	Manager share	Low edu. share	Med edu. share	High edu. share	Young worker share	Old worker share	Permanent worker share
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	1,060	1,060	1,060	1,060	1,060	1,060	1,060	1,060	1,060
Sample size control	1,116	1,116	1,116	1,116	1,116	1,116	1,116	1,116	1,116

Notes: Results from the RDD estimates using a local randomization approach with an analysis window of [5,5] around the cutoff (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 nonstandard 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 Calonico et al. (2016).

Table 11: Additional robustness checks: fuzzy RDD, donut-hole and linear specification (RIL-INAPP panel of Italian firms).

	(1)	(2)	(3)	(4)	(5)	(6)
	ER	Robots	Advance digital tools	ICT Investments	Training rate	Process innovations
<b>A. Fuzzy RDD</b>						
Point estimate		0.072	0.615	0.281	0.349	0.599
p-value		0.438	0.008	0.089	0.067	0.007
Window		[-5, 5]	[-5, 5]	[-5, 5]	[-5, 5]	[-5, 5]
Sample size treated		1,170	1,170	1,154	1,030	1,170
Sample size control		1,242	1,242	1,233	1,114	1,242
<b>B. Donut-hole specification</b>						
Point estimate	0.123	-0.004	0.047	0.056	0.017	0.063
p-value	0.000	0.792	0.064	0.002	0.439	0.006
Window	[-5, 5]	[-5, 5]	[-5, 5]	[-5, 5]	[-5, 5]	[-5, 5]
Sample size treated	627	632	632	623	545	632
Sample size control	941	959	959	952	862	959
<b>C. Linear adjustment (p=1)</b>						
Point estimate	0.046	0.015	0.010	-0.018	0.045	0.054
p-value	0.000	0.089	0.625	0.235	0.013	0.002
Window	[-5, 5]	[-5, 5]	[-5, 5]	[-5, 5]	[-5, 5]	[-5, 5]
Sample size treated	1,157	1,170	1,170	1,154	1,030	1,170
Sample size control	1,221	1,242	1,242	1,233	1,114	1,242

Notes: Results from the RDD estimates using a local randomization approach with an analysis window of [5,5] around the cutoff. Estimates based on RIL-INAPP panel of Italian. Panel A: fuzzy RDD estimates where ER is the endogeneous treatment variable (two-stage least squares statistic). Panel B: estimates from a donut-hole specification, excluding firms employing 14-16 employees. 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 nonstandard 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 Calonico et al. (2016).



## Appendix

### A.1 Correlation between ER and advanced technologies: additional results from EU workplaces

Table A.1.1: Robots, advanced digital tools and types of ER.

VARIABLES	(1) Robots	(2) Advanced digital tools
ER type: trade unions	0.020** (0.008)	0.033*** (0.011)
ER type: works councils	0.017* (0.009)	0.053*** (0.012)
ER type: other types of ER body	0.002 (0.009)	0.024* (0.014)
Observations	18,888	20,216
R-squared	0.171	0.134
Country + industry dummies	Yes	Yes
Establishment-level controls	Yes	Yes
Workforce composition	Yes	Yes
Competitive/Uncertain environment	Yes	Yes
Manager's controls	Yes	Yes

Notes: Estimates obtained from LPM models with robust standard errors in parentheses. In column (1), the dependent variable is a dummy variable indicating whether the establishment uses robots, i.e. programmable machines that are capable of carrying out a complex series of actions automatically. In column (2), the dependent variable is a dummy variable indicating whether the establishment uses advanced 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 characteristics (gender, position). \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

Table A.1.2: Robots, advanced digital tools and ER in countries with high/low employment protection.

VARIABLES	(1)	(2)	(3)	(4)
	Robots		Advanced digital tools	
	(Low EPL)	(High EPL)	(Low EPL)	(High EPL)
ER	0.021** (0.008)	0.009 (0.008)	0.045*** (0.012)	0.031*** (0.012)
Observations	8,250	10,638	8,839	11,377
R-squared	0.187	0.159	0.131	0.140
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 obtained from LPM models with robust standard errors in parentheses. In columns (1)-(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)-(4), the dependent variable is a dummy variable indicating whether the establishment uses advanced digital tools for analysing data collected at this establishment or from other sources to improve the processes of production or service delivery. Sample split based on whether the establishment is located in a country where the 2019 OECD EPL indicator of strictness of employment protection on individual and collective dismissals (regular contracts) is below (low EPL) or above (high EPL) the median value in OECD countries. Establishment-level controls: plant size, plant age, multi-site, 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 characteristics (gender, position). \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

Table A.1.3: Robots, advanced digital tools and ER: sample split based on degree of centralization (high/low) of the wage-setting process.

VARIABLES	(1)	(2)	(3)	(4)
	Robots		Advanced digital tools	
	(Low wage centralization)	(High wage centralization)	(Low wage centralization)	(High wage centralization)
ER	0.002 (0.008)	0.022*** (0.008)	0.018 (0.012)	0.056*** (0.012)
Observations	9,347	9,541	10,064	10,152
R-squared	0.133	0.206	0.135	0.136
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 obtained from LPM models with robust standard errors in parentheses. In columns (1)-(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)-(4), the dependent variable is a dummy variable indicating whether the establishment uses advanced digital tools for analysing data collected at this establishment or from other sources to improve the processes of production or service delivery. The degree of centralization of wage setting systems measured as the average incidence of higher-level wage bargaining (industry, region or national level) in each industry-country cell. Sample split based on whether the establishment is located in a industry-country cell below or above the median value of wage centralization. Establishment-level controls: plant size, plant age, multi-site, 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 characteristics (gender, position). \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.



Table A.1.4: Robots, advanced digital tools and ER in rapidly-ageing and slowly-ageing countries.

VARIABLES	(1)	(2)	(3)	(4)
	Robots		Advanced digital tools	
	(Rapidly-aging)	(Slowly-aging)	(Rapidly-aging)	(Slowly-aging)
ER	0.020** (0.009)	0.009 (0.007)	0.043*** (0.013)	0.031*** (0.011)
Observations	9,262	9,626	9,965	10,251
R-squared	0.166	0.179	0.139	0.133
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 obtained from LPM models with robust standard errors in parentheses. In columns (1)-(3), the dependent variable is a dummy variable indicating whether the establishment uses robots, i.e. programmable machines that are capable of carrying out a complex series of actions automatically. In columns (4)-(6), the dependent variable is a dummy variable indicating whether the establishment uses advanced digital tools for analysing data collected at this establishment or from other sources to improve the processes of production or service delivery. Estimates reported in columns (1) and (4) control for a dummy variable equal to 1 if the fraction of employees aged 50+ is greater than 60% (information merged at the size-industry-country cell using ECS 2013). In columns (2)-(3) and (5)-(6), sample split based on whether the establishment is located in rapidly-ageing (above median) or slowly-ageing country (below median). The indicator of ageing is the 1950-1990 change in the ratio of older workers (who are above the age of 54) to middle-aged workers (between the ages of 20 and 54) computed from UN Population Statistics. Establishment-level controls: plant size, plant age, multi-site, 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 characteristics (gender, position). \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

Table A.1.5: Robots, advanced digital tools and ER in sectors with different task composition.

VARIABLES	(1)	(2)	(3)	(4)
	Robots		Advanced digital tools	
	(Good tasks)	(Bad tasks)	(Good tasks)	(Bad tasks)
ER	0.004 (0.008)	0.023*** (0.008)	0.034*** (0.013)	0.041*** (0.011)
Observations	8,869	10,019	9,438	10,778
R-squared	0.175	0.176	0.131	0.141
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 obtained from LPM models with robust standard errors in parentheses. In columns (1)-(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)-(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. Data from EWCS 2005 is used to compute a metrics of “bad tasks”. The latter involve: i) tiring or painful positions; ii) lifting or moving people; iii) repetitive hand or harm movements. Task composition measured as the average incidence of bad tasks in each industry-country cell. Sample split based on whether the establishment is located in a industry-country cell below (good task group) or above (bad task group) the industry median value of bad tasks. 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 characteristics (gender, position). \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

## A.2 RD analysis using RIL-INAPP panel of Italian firms: robustness and validation checks

### A.2.1 Window selection

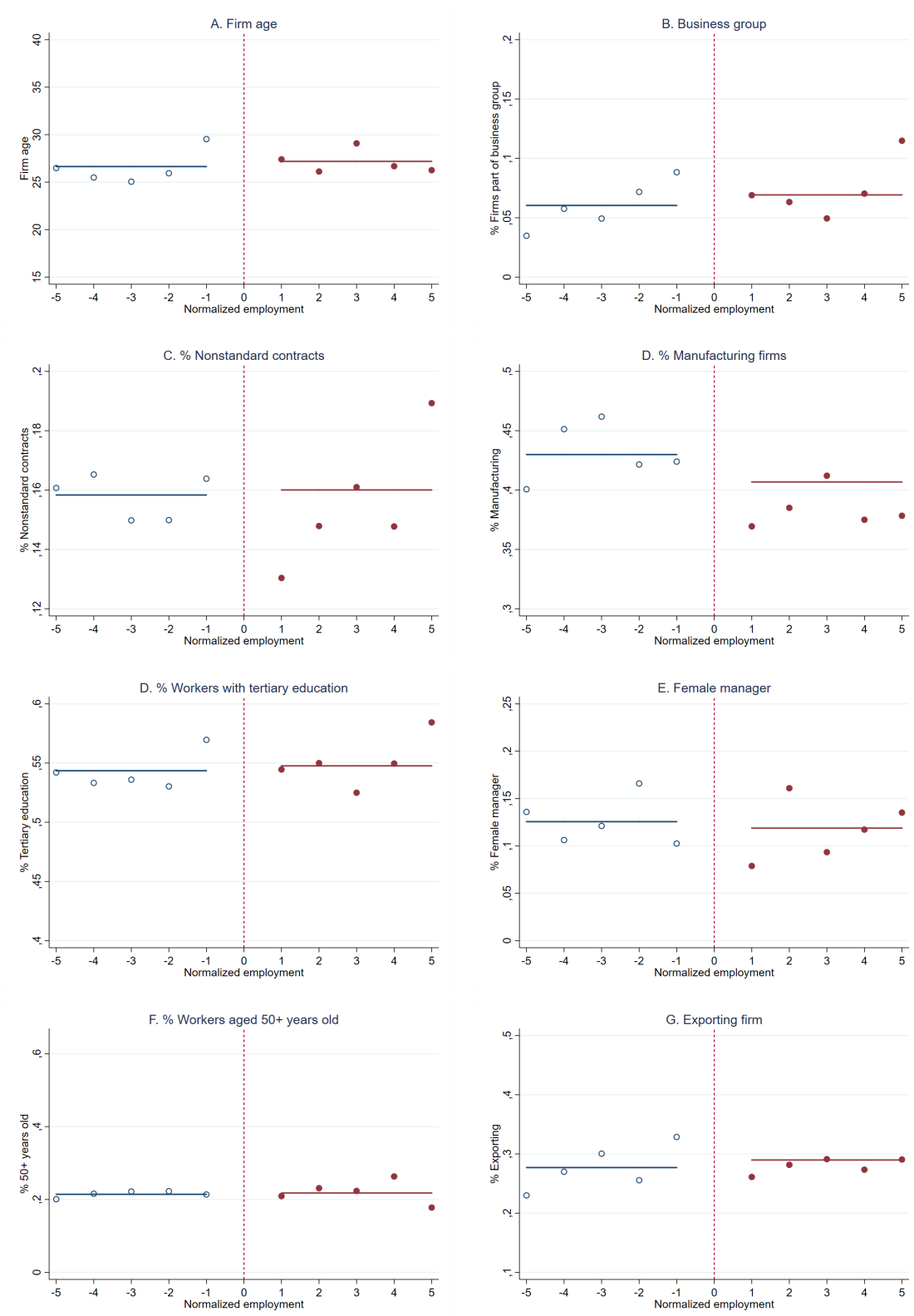
Table A.2.1: Window selection based on covariates.

WINDOW	(1) Minimum p-value	(2) Covariate with minimum p-value	(3) Obs < $c$	(4) Obs $\geq c$
1	0.264	Share of higher education	283	538
2	0.299	Business group	506	712
3	0.417	Manufacturing firm	729	894
4	0.223	Manufacturing firm	955	1022
5	0.260	Manufacturing firm	1242	1170
6	0.031	Exporting firm	1507	1297
7	0.003	Exporting firm	1815	1411
8	0.000	Exporting firm	2135	1530
9	0.000	Business group	2458	1633
10	0.000	Business group	2863	1749
11	0.000	Business group	3389	1838
12	0.000	Firm age	4028	1931
13	0.000	Firm age	4839	2031
14	0.000	Firm age	5652	2115
15	0.000	Firm age	6662	2209

Notes: Results from the selection of the optimal bandwidth (window) using RIL-INAPP panel of Italian firms. Included covariates: firm age, share of nonstandard 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. Optimal window is estimated with the Stata software *rdwinselect* developed by Calonico et al. (2016).  $c$  denotes the cutoff.

## A.2.2 Predetermined covariates

Figure A.2.1: RD plots: covariates (RIL-INAPP panel)



Notes: *rdplots* of the incidence of employee representation (panel A), use of robots (panel B) and use of data analytics (panel C). Normalized employment is reported on the horizontal axis, i.e. zero corresponds to the firm size threshold of 15 employees. RD-plots restricted to chosen optimal window  $[-5, 5]$  with polynomial degree = 0 and a uniform kernel.

Table A.2.2: Local-randomization analysis for covariates.

	(1)	(2)	(3)	(4)	(5)
	Mean of controls	Mean of treated	Diff-in-Means Stat	p-value	Obs.
Firm age	26.640	27.185	0.545	0.630	2412
Business group	0.060	0.069	0.009	0.402	2412
Share of nonstandard contracts	0.158	0.160	0.002	0.824	2412
Manufacturing firms	0.430	0.407	-0.023	0.260	2412
Share of workers w/tertiary edu.	0.543	0.548	0.004	0.739	2412
Female manager	0.126	0.119	-0.007	0.620	2412
Exporting firms	0.277	0.290	0.013	0.489	2412
Share of workers aged 50+	0.214	0.218	0.004	0.637	2412

Notes: Diff-in-means test statistics for the RDD covariates using the optimal window  $[-5, 5]$ . Estimates based on RIL-INAPP panel of Italian firms. Optimal window determined using the following covariates: firm age, share of nonstandard 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 Calonico et al. (2016).

### A.2.3 Sensitivity to window choice

Table A.2.3: Sensitivity of randomization-based RD results: ER and automation technologies for different window choices.

	(1)	(2)	(3)	(4)
	ER	Robots	Advance digital tools	ICT Investments
<b>[-3, 3]</b>				
Point estimate	0.084	0.007	0.039	0.017
p-value	0.000	0.562	0.114	0.373
Sample size treated	884	894	894	881
Sample size control	719	729	729	724
<b>[-7, 7]</b>				
Point estimate	0.116	0.019	0.050	0.039
p-value	0.000	0.009	0.001	0.003
Sample size treated	1,392	1,411	1,411	1,395
Sample size control	1,779	1,815	1,815	1,802
<b>[-9, 9]</b>				
Point estimate	0.123	0.023	0.059	0.051
p-value	0.000	0.001	0.000	0.000
Sample size treated	1,613	1,633	1,633	1,614
Sample size control	2,412	2,459	2,459	2,444
<b>[-11, 11]</b>				
Point estimate	0.135	0.028	0.074	0.061
p-value	0.000	0.000	0.000	0.000
Sample size treated	1,813	1,838	1,838	1,818
Sample size control	3,310	3,390	3,390	3,373

Notes: Results from the RDD estimates using a local randomization approach and alternative analysis windows around the cutoff (local-constant polynomial approximation using a uniform kernel). Outcome variables defined as in Table 7. Models are estimated with the Stata software *rdrandinf* developed by Calonico et al. (2016).

## A.2.4 Placebo cutoffs

Table A.2.4: Placebo cutoffs.

	(1)	(2)	(3)	(4)
	ER	Robots	Advance digital tools	ICT Investments
<b>A. Fake cutoff: 10 employees</b>				
Point estimate	0.034	0.027	0.045	0.030
p-value	0.000	0.000	0.004	0.013
Window	[-5, 5]	[-5, 5]	[-5, 5]	[-5, 5]
Sample size treated	1,549	1,577	1,577	1,563
Sample size control	1,588	1,622	1,622	1,615
<b>B. Fake cutoff: 25 employees</b>				
Point estimate	0.010	0.006	0.015	0.021
p-value	0.691	0.742	0.616	0.391
Window	[-5, 5]	[-5, 5]	[-5, 5]	[-5, 5]
Sample size treated	568	576	576	573
Sample size control	602	611	611	608
<b>C. Fake cutoff: 35 employees</b>				
Point estimate	0.013	-0.004	0.008	0.001
p-value	0.713	0.910	0.835	1.000
Window	[-5, 5]	[-5, 5]	[-5, 5]	[-5, 5]
Sample size treated	400	402	402	397
Sample size control	413	415	415	411

Notes: Results from the RDD estimates using a local randomization approach with an analysis window of [5,5] around placebo cutoff points (local-constant polynomial approximation using a uniform kernel). Estimates based on RIL-INAPP panel of Italian firms. Outcome variables defined as in Table 7. Optimal window determined using the following covariates: firm age, share of nonstandard 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 Calonico et al. (2016).

Table A.2.5: Placebo cutoffs General.

	5	6	7	8	9	15	21	22	23	24	25	26	27	28	29	30
<b>A. ER</b>																
Point estimate	0,029	0,035	0,038	0,036	0,035	0,093	0,028	0,025	-0,018	0,008	0,010	0,030	0,055	0,072	0,115	0,083
p-value	0,000	0,000	0,000	0,000	0,000	0,000	0,176	0,285	0,442	0,777	0,691	0,241	0,043	0,010	0,000	0,002
Sample size treated	2.786	2.966	2.584	2.148	1.833	1.221	829	750	689	626	602	567	533	513	494	475
Sample size control	1.868	1.693	1.598	1.499	1.477	1.157	656	625	612	578	568	534	535	517	497	499
<b>B. Robots</b>																
Point estimate	0,007	0,013	0,014	0,013	0,017	0,007	0,028	0,025	0,022	0,026	0,006	-0,004	0,008	0,008	0,010	0,033
p-value	0,039	0,001	0,007	0,015	0,004	0,466	0,017	0,048	0,088	0,060	0,742	0,810	0,625	0,728	0,569	0,065
Sample size treated	3.799	3.194	2.704	2.214	1.883	1.242	835	759	699	636	611	579	541	520	501	482
Sample size control	1.909	1.730	1.630	1.532	1.507	1.170	668	634	620	585	576	537	538	520	499	502
<b>C. Advanced digital tools</b>																
Point estimate	0,123	0,098	0,074	0,060	0,041	0,057	0,005	0,019	0,025	0,028	0,015	0,023	0,012	0,021	0,022	0,012
p-value	0,000	0,000	0,000	0,000	0,011	0,005	0,861	0,510	0,363	0,334	0,616	0,442	0,697	0,552	0,509	0,758
Sample size treated	3.799	3.194	2.704	2.214	1.883	1.242	835	759	699	636	611	579	541	520	501	482
Sample size control	1.909	1.730	1.630	1.532	1.507	1.170	668	634	620	585	576	537	538	520	499	502
<b>D. ICT Investments</b>																
Point estimate	0,054	0,042	0,030	0,032	0,032	0,028	0,023	0,014	0,022	0,016	0,021	0,008	0,004	0,015	0,036	0,044
p-value	0,000	0,000	0,003	0,006	0,007	0,081	0,292	0,546	0,343	0,517	0,391	0,777	0,881	0,620	0,193	0,101
Sample size treated	3.788	3.184	2.696	2.208	1.877	1.233	824	750	694	630	608	575	537	514	498	479
Sample size control	1.900	1.720	1.620	1.521	1.496	1.154	664	628	614	582	573	535	536	519	495	498

Notes: Results from the RDD estimates using a local randomization approach with an analysis window of [5,5] around placebo cutoff points (local-constant polynomial approximation using a uniform kernel). Estimates based on RIL-INAPP panel of Italian firms. Outcome variables defined as in Table 7. Optimal window determined using the following covariates: firm age, share of nonstandard 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 Calonico et al. (2016).

### A.2.5 Confounding policies

Table A.2.6: Confounding policies: employment protection and short-time work schemes.

	(1)	(2)	(3)	(4)
	ER	Robots	Advance digital tools	ICT Investments
<b>A. Excluding firms affected by the Jobs Act</b>				
Point estimate	0.088	0.007	0.055	0.027
p-value	0.000	0.423	0.012	0.091
Window	[-5, 5]	[-5, 5]	[-5, 5]	[-5, 5]
Sample size treated	965	976	976	962
Sample size control	1,040	1,055	1,055	1,049
<b>B. Excluding firms using CIG</b>				
Point estimate	0.084	0.008	0.057	0.028
p-value	0.000	0.425	0.005	0.066
Window	[-5, 5]	[-5, 5]	[-5, 5]	[-5, 5]
Sample size treated	1,070	1,083	1,083	1,068
Sample size control	1,146	1,167	1,167	1,159

Notes: Results from the RDD estimates using a local randomization approach with an analysis window of [5,5] around placebo cutoff points (local-constant polynomial approximation using a uniform kernel). Estimates based on RIL-INAPP panel of Italian firms. Outcome variables defined as in Table 7. In Panel A, we exclude firms reporting that the enactment of the 2015 Jobs Act changed their hiring policy. We assume this is the group of firms for which firing restrictions around the 15 employees threshold were more binding. In panel B, we exclude firms using either Cassa Integrazione Guadagni Ordinaria (CIGO) or Cassa Integrazione Guadagni Straordinaria (CIGS) in 2014. Optimal window determined using the following covariates: firm age, share of nonstandard 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 Calonico et al. (2016).



### A.3 Complementary RDD analysis: EU workplaces

As a complement to the regression discontinuity design using Italian data presented in section 4, we implement a similar analysis based on EU workplace-level data from the European Company Survey. Overall, the results are broadly consistent with the Italian case study. However, given the caveats discussed below, we consider the RDD using EU data as a complementary empirical exercise rather than our preferred approach.

**A. Institutions and identification.** We use a regression discontinuity design (RDD) and exploit size-contingent regulations governing the operation of ER at the workplace level in most EU countries. We expect these workplace size thresholds provide some exogenous variation in the presence of employee representation. Given the the existence of multiple country-specific cutoffs, we normalize the running variable so that all workplaces face the same common cutoff value at zero.

While size cutoffs do not perfectly determine treatment (ER presence), as the minimums allow employee representation to be established only if requested by employees, they create a discontinuity in the probability of receiving treatment. Given the fact that ECS covers workplaces employing at least 10 employees, we exclude observations from countries where the size cutoff for triggering ER rights is below 10 employees. We also exclude observations from Malta and Cyprus due to low number of cases. In Table A.3.1, we provide detailed information on ER rules by country. To construct this table, we use information from CBR-LRI (labor regulation) dataset (Adams et al., 2017) complemented by information on national industrial systems collected by ETUI ([www.worker-participation.eu/](http://www.worker-participation.eu/)). See Fulton, 2020).

**B. Caveats.** There are several limitations associated with this exercise. First, the lack of longitudinal workplace-level information forces us to measure the presence of ER, the forcing variable (establishment size) and the use of automation technologies contemporaneously. This raises obvious concerns about potential feedback loops between processes involving the forcing variable (size), the treatment and the use of technology. In our main exercise using Italian data, we mitigated this problem by using lagged information on firm size and other covariates. Second, conducting the RDD analysis using workplace-data from many different countries involves the harmonization of complex legal rules regarding the precise conditions in which workers can trigger representation rights at the local level. This is relatively easier operation when the analysis is restricted to a single country. For instance, as ECS collects information on employment figures at the workplace level, we do not have information on firm size in the case of multi-site firms. As legal size thresholds to trigger ER rights in certain countries are defined at the firm level, this may lead to measurement errors in the specification of the treatment status. We circumvent this problem by reporting additional estimates for single-site firms in which the treatment status can be unambiguously specified. Moreover, legislation in some countries regulates trade union representation and works councils at the workplace level differently. Legal thresholds regarding trade union representation usually do not depend on the total number of employees employed in the workplace, but on a minimum number of union members. Unfortunately, information about union membership is not available in ECS, making impossible to capture these nuances in a precise way. Finally, in some countries the possibility of triggering ER rights is not completely absent in workplaces below the legal size cutoff, but these rights are usually stronger for establishments above the threshold. In principle, this would make more it difficult to observe a discontinuity in ER presence (in the extensive margin) at the cutoff.

**C. Specification and results.** Given the fact that our forcing variable (workplace size) is discrete and has few mass points (i.e. values of the variable that are shared by many units) in its support<sup>34</sup>, we rely on the alternative local randomization approach to RDD, which stipulates that treatment assignment may be approximated by a local random experiment near the cutoff  $c$  (Lee, 2008; Cattaneo et al., 2015, 2016).<sup>35</sup>

An important procedural step is to select the window around the size cutoff where the presence of ER can be plausibly assumed to have been as-if randomly assigned. To do this, we use information provided by relevant covariates. To determine the optimal window, we use the following covariates: workplace age, dummy variables indicating whether the firm made a profit in the previous year, whether there were changes in the ownership structure, and whether the workplace operates in environments characterized by very predictable demand and very competitive markets. In Table A.3.2, 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. The resulting p-values are above 0.15 in all windows between the minimum window  $[-1, 1]$  and  $[-4, 4]$ . Then, the p-value drops to 0.117, below the suggested 0.15 threshold. Therefore, we perform the local randomization analysis in the chosen window  $[-4, 4]$ . First, we check for first stage effects, i.e. whether there is a discontinuity in the incidence of ER around the cutoff. In column (1) of Table A.3.3 we report a significant 4.6 percentage points difference in the mean incidence of ER in the chosen window, with a p-value of 0.036. Figure A.3.1 (Panel A) also shows clear evidence of a discontinuity in the presence of ER at the cutoff point.

Having documented that there is a discontinuity in the presence of ER around the cutoff, we now turn to our outcome of interest, i.e. the utilization of advanced technologies. In column (2) of Table A.3.3, we report estimates concerning the utilization of robots. We do not find significant discontinuity in the use of this specific technology around the cutoff. Finally, in column (3), we report a highly significant and sizeable difference of roughly 9 percentage points in the use of advanced digital tools. This is also consistent with graphical evidence reported in Figure A.3.1 (Panel B and C). Similar results are obtained when the analysis is restricted to single-site firms.

**D. 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 cutoff. 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  $[-4, 4]$ . Results are reported in Table A.3.4 and Figure A.3.2. Reassuringly, we do not find evidence of treatment effects for any of these characteristics. Second, we analyze the density of the forcing variable within our selected window  $[-4, 4]$ , i.e. whether the number of establishments just above the cutoff is similar to the number of establishments just below the cutoff. Sorting around the cutoff may occur if establishments manipulate their size in order to block employees' attempts to trigger ER rights. The p-value of a binomial test is 0.158, indicating that there is no evidence of

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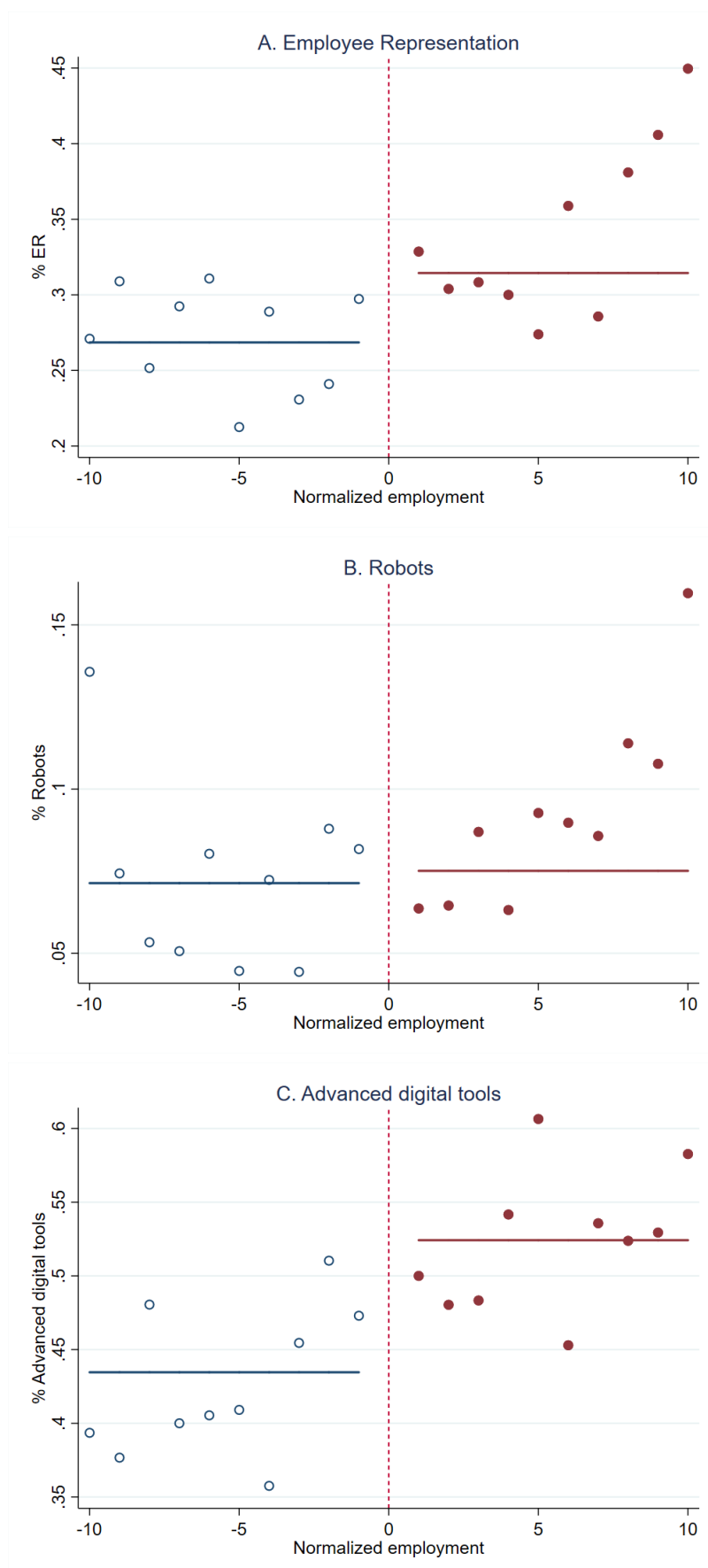
<sup>34</sup>We count 15900 observations with non-missing values of the forcing variable. However, the variable is discrete and has mass points, with 615 unique values. This would be the effective number of observations used in continuity-based RDD methods.

<sup>35</sup>For practical implementation, we use the functions *rdwinselect* and *rdrandinf*, part of the the *rdlocrand* package developed by Cattaneo et al. (2015).

sorting around the cutoff in the chosen window (Cattaneo et al., 2017). Third, we consider placebo cutoff values. No effect should be found at any of these “fake” cutoffs. We analyze the case of  $c=10, 30$ , finding no evidence of treatment effects.

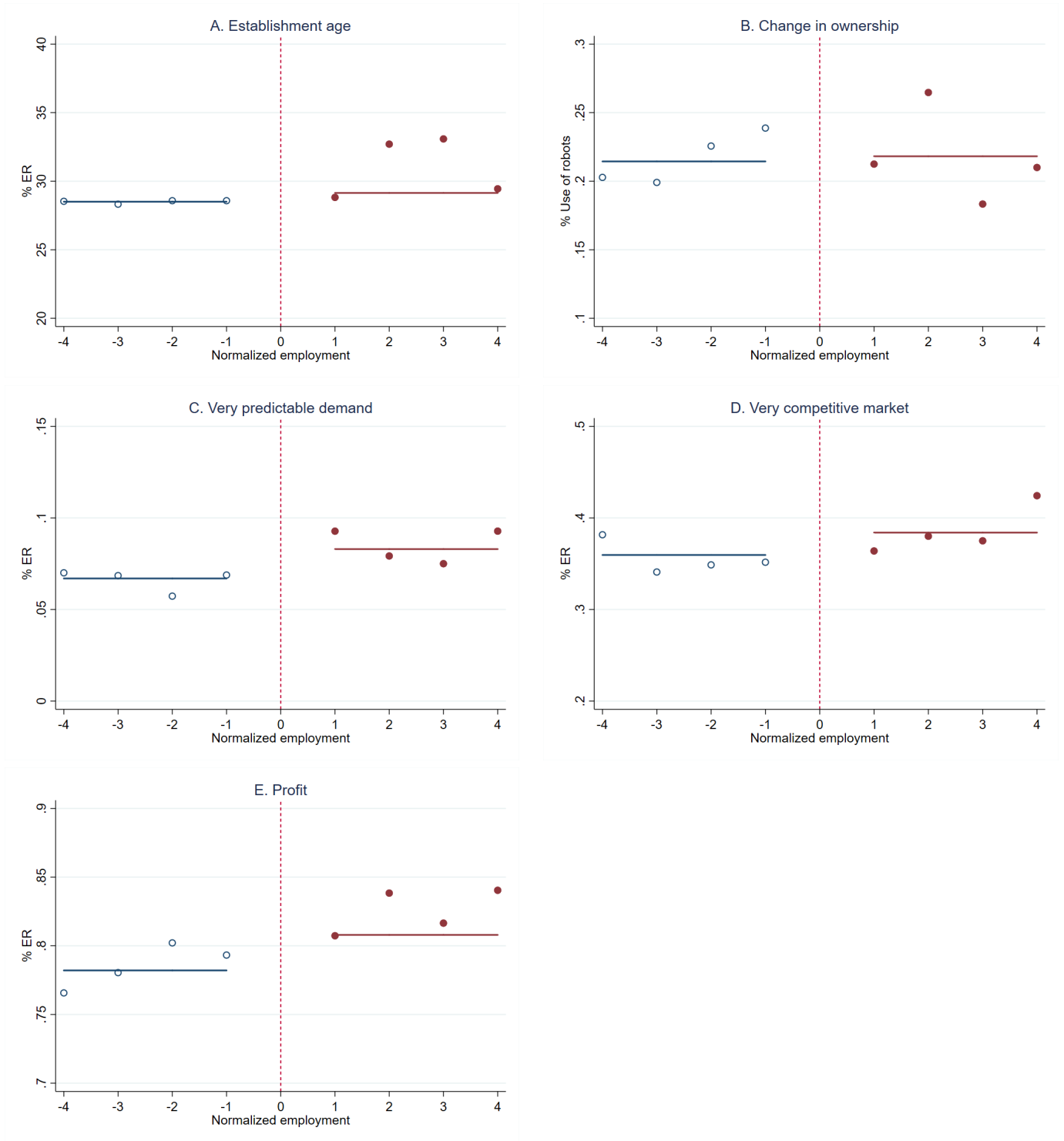
Finally, we consider the sensitivity of the results to our window choice. We replicate the local-randomization analysis for both smaller and larger windows than our selected window. We consider one smaller windows,  $[-3, 3]$ , and three larger windows,  $[-5, 5]$ ,  $[-11, 11]$  and  $[-15, 15]$ . As discussed by Cattaneo et al. (2015), the analysis of 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.3.5 presents the results from this exercise. Overall, the main findings hold for both smaller and larger windows. The only exception refers to the effect on robot usage, which appears to be statistical significant in larger windows. This again suggests that the lack of significant effects in terms of robot usage may relate to the fact that our RDD analysis is restricted to relatively small workplaces when the distribution of robots is highly concentrated in large firms.

Figure A.3.1: RD plots: ER, robot usage and data analytics



Notes: *rdplots* of the incidence of employee representation (panel A), use of robots (panel B) and use of data analytics (panel C). Normalized employment is reported on the horizontal axis, i.e. zero corresponds to the country-specific firm size threshold. *Rdplots* restricted to chosen window  $[-6, 6]$  with polynomial degree = 0 and a uniform kernel.

Figure A.3.2: RD plots: covariates



Notes: *rdplots* of covariates used to select the optimal window. Normalized employment is reported on the horizontal axis, i.e. zero corresponds to the country-specific firm size threshold. RD-plots restricted to chosen optimal window  $[-4, 4]$  with polynomial degree = 0 and a uniform kernel.

Table A.3.1: Country-specific firm size cutoffs.

COUNTRY	Firm-size cutoff (num. of employees)
Austria	5
Belgium	50
Bulgaria	50
Croatia	20
Cyprus	30
Czechia	10
Denmark	35
Estonia	30
Finland	20
France	50
Germany	5
Greece	50
Hungary	50
Ireland	50
Italy	15
Latvia	No threshold
Lithuania	15
Luxembourg	15
Malta	50
Netherlands	50
Poland	50
Portugal	No threshold
Romania	20
Slovakia	50
Slovenia	20
Spain	50
Sweden	No threshold
UK	50

Notes: Information is based on Fulton (2020) National Industrial Relations, an update. labor Research Department and ETUI.

Table A.3.2: Window selection based on covariates.

	(1)	(2)	(3)	(4)
WINDOW	Minimum p-value	Covariate with minimum p-value	Obs < $c$	Obs $\geq c$
1	0.536	Very predictable demand	203	567
2	0.327	Very predictable demand	386	663
3	0.348	Very competitive market	590	772
4	0.196	Made a profit in 2018	934	864
5	0.117	Made a profit in 2018	1206	1012
6	0.125	Very competitive market	1336	1168
7	0.171	Very competitive market	1496	1275
8	0.090	Plant age	1642	1351
9	0.048	Plant age	1976	1412
10	0.029	Plant age	2118	1525
11	0.009	Plant age	2196	1722
12	0.027	Plant age	2274	1772
13	0.033	Very competitive market	2320	1831
14	0.069	Very competitive market	2492	1875
15	0.024	Very competitive market	2608	1965

Notes: Table reports the statistical results of the selection of the optimal bandwidth (window). Included covariates: plant age and dummy variables indicating whether the firm made a profit in the previous year, whether there were changes in the ownership structure, and whether the establishment operates in environments characterized by very predictable demand and very competitive markets. Optimal window is estimated with the Stata software *rdwinselect* developed by Calonico et al. (2016).  $c$  denotes the cutoff.

Table A.3.3: Randomization-based approach: main results.

	(1)	(2)	(3)
	ER	Robots	Advanced digital tools
<b>A. All establishments</b>			
Point estimate	0.046	0.004	0.090
p-value	0.036	0.805	0.000
Window	[-4, 4]	[-4, 4]	[-4, 4]
Polynomial degree	0	0	0
Sample sized treated	935	879	929
Sample sized control	998	911	994
<b>B. Single-site firms</b>			
Point estimate	0.047	0.008	0.085
p-value	0.025	0.601	0.000
Window	[-4, 4]	[-4, 4]	[-4, 4]
Polynomial degree	0	0	0
Sample sized treated	730	684	726
Sample sized control	776	700	772

Notes: Table reports the results from the RDD estimation. Included covariates: plant age and dummy variables indicating whether the firm made a profit in the previous year, whether there were changes in the ownership structure, and whether the establishment operates in environments characterized by very predictable demand and very competitive markets. Results are estimated with the Stata software *rdrandinf* developed by Calonico et al. (2016).

Table A.3.4: Local-randomization analysis for covariates.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Mean of controls	Mean of treated	Diff-in-Means Stat	p-value	Obs.
Plant age	28.505	29.143	0.638	0.614	1919
Change in ownership	0.214	0.218	0.004	0.892	1933
Predictable demand	0.067	0.083	0.016	0.208	1902
Very competitive market	0.360	0.384	0.024	0.273	1917
Profit	0.782	0.808	0.026	0.162	1830

Notes: Table reports the diff-in-means test statistics across the cutoff for the RDD covariates. Included covariates: plant age and dummy variables indicating whether the firm made a profit in the previous year, whether there were changes in the ownership structure, and whether the establishment operates in environments characterized by very predictable demand and very competitive markets. Results obtained with the Stata software *rdwinselect* developed by Calonico et al. (2016).

Table A.3.5: Sensitivity of randomization-based RD results: ER and automation technologies for different window choices.

	(1)	(2)	(3)
	ER	Robots	Advanced digital tools
<b>Optimal window: [-4,4]</b>			
Point estimate	0.046	0.004	0.090
p-value	0.036	0.805	0.000
Polynomial degree	0	0	0
Sample sized treated	935	879	929
Sample sized control	998	911	994
<b>[-3, 3]</b>			
Point estimate	0.059	0.006	0.044
p-value	0.010	0.757	0.102
Polynomial degree	0	0	0
Sample sized treated	835	784	833
Sample sized control	638	593	636
<b>[-5, 5]</b>			
Point estimate	0.053	0.012	0.107
p-value	0.003	0.261	0.000
Polynomial degree	0	0	0
Sample sized treated	1092	1030	1084
Sample sized control	1285	1180	1280
<b>[-11, 11]</b>			
Point estimate	0.077	0.019	0.113
p-value	0.000	0.034	0.000
Polynomial degree	0	0	0
Sample sized treated	1872	1748	1861
Sample sized control	2366	2168	2358
<b>[-15, 15]</b>			
Point estimate	0.067	0.019	0.116
p-value	0.000	0.018	0.000
Polynomial degree	0	0	0
Sample sized treated	2135	1997	2120
Sample sized control	2831	2611	2822

Notes: Table reports results obtained with alternative windows. Covariates included: multi-site, plant age, change in ownership, very predictable demand, very competitive market. Results are estimated with the Stata software *rdrandinf* developed by Calonico et al. (2016).