Contested Transparency: Digital Monitoring Technologies and Worker Voice*

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Abstract

Advances in artificial intelligence and data analytics have notably expanded employers' monitoring and surveillance capabilities, facilitating the accurate observability of work effort. There is an ongoing debate among academics and policymakers about the productivity and broader welfare implications of digital monitoring (DM) technologies. In this context, many countries confer information, consultation and codetermination rights to employee representation (ER) bodies on matters related to the workplace governance of these technologies. Using a cross-sectional sample of more than 21000 European establishments, we document a positive association between ER and the utilization of DM technologies. We also find a positive effect of ER on DM utilization in the context of a local-randomization regression discontinuity analysis that exploits size-contingent policy rules governing the operation of ER bodies in Europe. We interpret these findings through the lens of a theoretical framework in which shared governance via ER create organizational safeguards that mitigate workers' negative responses to monitoring and undermines the disciplining effect of DM technologies.

Keywords: Digital-based monitoring, algorithmic management, HR analytics, transparency, innovation, worker voice, employee representation

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1 Introduction

Contested exchanges, like the provision of work effort in return for a wage inside firms, require *ex-post* enforcement mechanisms, which often include the monitoring of employee performance (Bowles and Gintis, 1988). While in the past such monitoring relied mostly on human interventions (e.g. guard labor, see Jayadev and Bowles, 2006), recent advancements in artificial intelligence and data analytics have opened a whole set of new possibilities to employers. Intelligent wearable devices such as smart cameras and electronic armbands, for instance, allow managers to collect real-time data about employees' every move (Head, 2014; Bernstein, 2017). Similarly, workplace surveillance software such as eye tracking and visual recognition tools enable the constant monitoring of employees' online activities, even when working from home (Aloisi and De Stefano, 2022).[1]

This unprecedented expansion of employers' digital monitoring (DM) capabilities has become a hotly contested issue. On the one hand, DM is expected to improve worker incentives by fostering the transparency, or accurate observability, of human work (Tapscott and Ticoll, 2003). On the other hand, the adoption of DM by profit-maximizing employers may negatively affect workforce wellbeing, entailing complicated implications in terms of employee dignity, privacy rights and social welfare (Kasy, 2023; Rogers, 2023). Artificial intelligence may enable intrusive monitoring practices merely oriented to shift rents away from workers towards employers without generating substantial productivity gains (Acemoglu, 2021; Acemoglu and Johnson, 2023).[2] Importantly, DM technologies may backfire if workers exhibit negative behavioural reactions (e.g. control aversion) to intensified monitoring systems (Falk and Kosfeld, 2006; Burdin et al., 2018; Herz and Zihlmann, 2021); and firms may hesitate to adopt them due to these potential detrimental effects. But then, a natural question to ask is how can organizations adopt DM without risking undermining employee motivation? In spite of growing attention and interest on these technologies, little is known about the institutional and organizational conditions affecting their implementation and impacts.

[1] Covid-19 and the associated expansion of work-from-home arrangements may have also influenced the development of digital-based monitoring technologies (Bloom et al., 2021).

[2] Indeed, the increasing reliance on surveillance capital has been offered as an explanation for the reduction in the labour share, wage inequality, unemployment of low-skill workers, and the productivity slowdown observed in many countries (Skott and Guy, 2007; Askenazy, 2021).

In this paper we address the following question: does the existence of employee representation (ER), and related collective bargaining procedures over DM utilization, help or hinder the adoption of these technologies? We propose a theoretical framework that takes the conflicting nature of work transparency at its core (i.e. contested transparency). More precisely, we develop a labour discipline model where a representative profit-maximizing employer interacts with a control-averse employee to carry out production. The employer chooses the level of efficiency wage and decides whether to invest in a DM technology in order to extract the highest possible level of noncontractible effort from the employee. DM investments affect equilibrium profits through four channels. First, the employer pays an *implementation cost*, which includes direct purchasing costs and costs related to the organizational restructuring required to operate the new technology. Second, the introduction of DM has ambiguous effects on worker effort. On the one hand, DM facilitates effort extraction by improving work observability and enhancing the credibility of employer's dismissal threats (*disciplining effect*). On the other hand, the introduction of DM tools triggers an *adverse commitment effect* from control-averse workers, as monitoring undermines intrinsic motivations and trust towards the employer.[3]

In our model, ER bodies negotiate and enforce data governance rules that impose limits on employers' discretion to use DM-generated data and help to preserve workers' "zones of privacy" (Bernstein, 2017). The presence of ER has opposing effects on employer's willingness to invest in DM. First, ER reduces the disciplining effect of DM by restricting the ability of employers to use the information collected by DM tools for punitive purposes. Second, ER mitigates workers' negative behavioural reactions to monitoring by improving the accountability of DM systems (e.g. enforcement of safeguard procedures on how monitoring data is used by the firm) and bargaining over complementary changes in work systems and practices (e.g. training).[4] Therefore, the net effect of ER ultimately rests on the relative strength of these mechanisms.

Our empirical analysis exploits rich workplace-level data covering most European

[3] As shown by a variety of studies in behavioural and organization research, monitoring and greater work transparency may trigger negative control-averse responses (Falk and Kosfeld, 2006; Burdin et al., 2018; Kosfeld, 2020; Herz and Zihlmann, 2021; Rudorf et al., 2018) and enter into conflict with a fundamental desire for privacy, fostering mistrust and hiding behaviours among workers (i.e. the "transparency paradox", see Bernstein, 2012, 2017).

[4] Qualitative evidence on actual labor-management negotiations over algorithmic management and digital monitoring tools in specific sectors seems to be consistent with the role assigned to ER in our model (Doellgast et al., 2022).

countries. We choose Europe as it is a perfect setting to test the role of collective negotiation in shaping the utilization of DM technologies. Indeed, in most countries there exist detailed legal prescriptions to protect privacy at the workplace, which are enforced through institutions of employee representation. In countries like Austria, Germany and Netherlands, for instance, the introduction and use of employee monitoring technologies is subject to the approval of works councils. In other countries, although the prescription is less stringent, workers can still enjoy significant information and consultation rights when a monitoring technology is about to be introduced by the employer. Moreover, all the EU member states must abide to the General Data Protection Regulation (GDPR), which disciplines the collection, use and transfer of personal data and sets out provisions that apply to all data-processing operations, including employee monitoring (Eurofound, 2020)

We rely on data retrieved from the last wave of the European Company Survey (2019), containing granular information on more than 21,000 establishments located in 28 countries. For each establishment the survey provides harmonized information on the presence of employee representative (ER) bodies, monitoring technologies and a wide range of management practices. The survey includes questions on whether the establishment uses data analytics to monitor employee performance.[5] Moreover, it reports detailed information about the ER structure alongside a large set of other establishment-level characteristics, including information on innovative performance (i.e. whether the establishment introduced new products and/or processes). The availability of such a wealth of information allows us to investigate both a) the relationship between the presence of collective bargaining procedures to negotiate the adoption and use of monitoring technologies and b) the effect of such technologies on innovation at the estblishment level.

Our empirical analysis documents the existence of a positive association between ER and the utilization of digital-based monitoring technologies. This positive association also holds in the context of a local-randomization regression discontinuity analysis in which we exploit size-contingent policy rules providing plausibly exogenous variation in the incidence of ER bodies across European workplaces. We thus find that worker voice institutions do not inhibit, and rather they seem to favor, the adoption of

[5] Using similar data from ECS, Bechter et al. (2022) identify firm-level characteristics and contextual factors correlated with the use of HR analytics to monitor employees. However, they do not analyze the role played by ER bodies in relation to the utilization of these technologies.

monitoring technologies.

The paper makes two main contributions.[6] Firstly, we contribute to the relatively thin literature on how worker voice institutions shape the future of work by influencing the process of adoption and implementation of advanced technologies at the workplace level. In a series of related contributions, Belloc et al. (2022) and Belloc et al. (2023) show that workplace employee representation is associated with greater adoption of advanced technologies and favors job designs that reduce workers' exposure to automation, enhancing labour-technology complementarities. In the German context, characterized by a well-known system of collective bargaining and employee representation in corporate decisions (Jäger et al., 2022), two recent studies show that workers exposed to automation receive additional training and transition to higher-skilled tasks within firms (Dauth et al., 2021; Battisti et al., 2023). Genz et al. (2019) show that the existence of works councils reduces the use of digital technologies, although the effect is reversed for plants employing a high share of workers performing physically demanding jobs.[7] None of these papers, however, focuses on how employee representation shapes the use of DM technologies. Interestingly, the idea of limiting employers' discretion in relation to the utilization of these technologies has been at the centre of recent policy debates. While several countries have conferred new codetermination rights to employee representatives with respect to these technologies (Eurofound, 2020), little is known about the actual impact of such regulatory frameworks. We show that restricting employers' authority through shared governance mechanisms does not obstruct the adoption of modern digital-based monitoring technologies.[8]

Secondly, we add to the literature on the use of employee monitoring systems within firms. Theoretically, the role of supervision and monitoring has been central to a range of approaches highlighting the conflicting nature of the labour process (Gintis, 1976; Bowles, 1985; Duda and Fehr, 1987; Skillman, 1988; Skott and Guy, 2007). According to this view, employers invest in technologies that increase the observability of

[6]Given our focus on digital monitoring, the paper also relates to the management literature on HR analytics (Tursunbayeva et al., 2018; Edwards et al., 2022; Angrave et al., 2016; Bechter et al., 2022) and algorithmic management (Benlian et al., 2022; Kellogg et al., 2020; Jarrahi et al., 2021; Meijerink and Bondarouk, 2021; Duggan et al., 2020).

[7]Presidente (2023) shows that labor-friendly institutions induce automation, particularly in sunk-cost intensive industries where employers are vulnerable to hold-up problems.

[8]Analyzing more traditional monitoring practices, such as formal performance evaluations and feedback interviews, Grund et al. (2023) show that works councils play a gatekeeper role, facilitating the adoption of these practices and increasing job satisfaction.

human work and enhance the credibility of the threat of dismissal in order to facilitate effort extraction. Conventional agency theory also stresses the importance of monitoring as an incentive device in principal-agent relationships (Alchian and Demsetz, 1972; Prendergast, 1999).[9] Our paper adds to this literature by providing a framework and evidence on the interplay between firm-level advanced monitoring practices and worker voice institutions

The remainder of the document is organised as follows. In Section 2, we develop our formal model. In Section 3, we present our main source of data and estimation sample. In Section 4, we present the main findings from our correlational analysis and regression discontinuity approach. Section 5 concludes.

2 The model

We analyze a two-stage, partial-equilibrium, labour-discipline model where a risk-neutral employer (she) interacts with a representative, control- and risk-averse employee (he). The employee's interest regarding non-wage job characteristics may be channelled through a workplace body of employee representation, in which case, the binary variable $E \in \{0, 1\}$ used in what follows equals 1 (0 otherwise).

2.1 Efficiency wage

At stage 1, the employer chooses the efficiency wage level $w > 0$ that elicits the worker's highest possible effort $e \geq 0$ at stage 2. Providing effort entails a disutility for the employee, as measured by the (quasi-convex) cost function $c(e)$ – with $c'(e) > 0$ and $c''(e) \geq 0$. In addition, the worker's (quasi-concave) output $y(e)$ – with $y'(e) > 0$ and $y''(e) \leq 0$ – is assumed to be observable, while effort is only imperfectly so depending on the level of monitoring efficiency that determines the probability $\mu \in \{0, 1\}$ that the employer "sees" the worker during the productive period. As common in efficiency wage models, the worker is fired when caught shirking, in which

[9]While these approaches predict a positive effect of monitoring on worker performance, empirical evidence is mixed. Some studies show that IT-based monitoring technologies reduce extreme forms of employee misconduct (e.g. theft) and improve performance in specific contexts (Hubbard, 2000; Duflo et al., 2012; Pierce et al., 2015). However, recent work has shown that the positive effect of performance monitoring on productivity may be short-lived in contexts of rapid depreciation of worker skills if managers are unable to make on-the-job training investments (Adhvaryu et al., 2022). Moreover,monitoring may induce negative behavioural responses in production environments characterized by task complexity and multidimensional performance (Belot and Schröder, 2016; Herz and Zihlmann, 2021).

case, he receives his outside option $w_0 \geq 0$.[10]

2.2 Worker's output

Following Beckmann and Kräkel (2022), we specify the worker's output as a binary, probabilistic function of his optimally chosen effort, that takes the specific functional form $y(e) \equiv \pi(e)y_H + (1-\pi(e))y_L$, with $0 \leq y_L < y_H$ and $\Delta \equiv y_H - y_L$. In this specification, high output y_H ("success") is realized with a probability $\pi \in (0,1)$ that increases endogenously (possibly at a decreasing rate) with the worker's effort, so that $\pi'(e) > 0$ and $\pi''(e) \leq 0$; while low output y_L ("failure") is realized with probability $1-\pi(e)$. This implies that the probability with which the employer observes low effort and fires the employee – realizing a state-contingent payoff equal to y_L – is given by $(1-\pi(e))\mu$, while the worker's shirking remains unnoticed with probability $(1-\pi(e))(1-\mu))$ – in which case, the employer's contingent payoff is given by $y_L - w$.

2.3 Digital monitoring

At stage 1, the employer must also decide whether to sink a specific investment $k(D) > 0$ and implement a discrete digital monitoring tool knowing that this will have four effects on the equilibrium profit $\Pi^*(D,E)$ she realizes after production takes place at stage 2. The magnitude of some of these effects may be moderated by the presence of workplace employee representation, which, as we discuss below, may limit the extent to which the technology's potential can be exploited.[11]

(i) *Implementation cost*—Implementing the digital monitoring technology requires

[10]We assume that the ER (when present) is not involved or does not affect the wage setting procedure. This may happen for two reasons. First, if the ER-set wage does not suffice to elicit the highest possible effort, its wage demand is not binding, and the employer finds it rational to raise the worker's compensation up to the efficient level. Second, ER bodies are often devoid of wage bargaining power, which in most cases (especially in Continental Europe) is concentrated in the hands of sectoral unions. Indeed, existing quasi-experimental studies find either no effects, or very small positive effects, of codetermination on wages (Jäger et al., 2022; Harju et al., 2021). Third, since the level of the minimum wage may affect workers' perception of what constitutes a fair wage (thus raising their reservation wage), firms may still have to pay an above-the-min efficiency wage to elicit labour effort (Falk et al., 2006). For consistency with the assumptions of the model, we conduct additional estimates excluding establishments reporting the existence of a collective wage agreement negotiated at the establishment or company level. Results reported in section 4.1 are robust to this modification (see Appendix Column 1 of Table A1).

[11]While the assumption of a discrete digital monitoring technology greatly simplifies the algebra without affecting the model's message qualitatively, it is also in line with the nature of the data we use for our empirical analysis, where the information on the firm-level adoption of these technologies is coded as a dummy variable.

investing a fixed amount $k > 0$ of (irrecoverable) resources, so that $k \equiv k(D)$ and $k(1) - k(0) > 0$.

(ii) *Disciplining effect*—DM-generated data on worker activity eases labour surveillance and enhances the credibility of dismissal threats by improving work transparency, so that $\mu \equiv \mu(D)$ and $1 > \mu(1) > \mu(0) > 0$.

(iii) *Commitment effect*—The use of digital monitoring increases the marginal disutility of effort, for instance, by reducing the sense of task commitment or undermining trust in the employer-employee relationship, so that $c \equiv c(e, D)$ and $c(e, 1) - c(e, 0) > 0 \quad \forall e > 0$.

(iv) *Productivity effect*—DM-generated data on worker activity can be used to improve work organization and therefore, average labor productivity, increasing the probability of high output at each employee's effort level, so that $\pi \equiv \pi(e, D)$ and $\pi(e, 1) - \pi(e, 0) > 0 \quad \forall e > 0$.

A few comments on some of these postulated effects are worth drawing. First, the definition of implementation costs in point (i) is willingly broad, including the technology's direct purchasing cost plus the costs of the required organizational adaptations. Importantly, empirical studies document that firms typically experience a lag between the time they purchase HR analytics systems and the time when the technology is finally used, suggesting that the implementation process of DM is indeed complex and costly (Aral et al., 2012).

Second, the control-aversion effect postulated in point (iii) is not new. Indeed, a variety of studies in behavioral and organizational research (Falk and Kosfeld, 2006; Burdin et al., 2018; Kosfeld, 2020; Herz and Zihlmann, 2021; Rudorf et al., 2018) have shown that too much transparency may trigger control-averse responses, documenting the existence of what has been called a "transparency paradox" (Bernstein, 2012, 2017).[12] Recently, Beckmann and Kräkel (2022) summarized two psychological mechanisms that may explain why it is reasonable to assume that workers are control-averse. On the one hand, monitoring may reduce the employees' sense of psychological ownership and task commitment (Reynolds, 1973; Cassar and Meier, 2018), making them

[12] A "control-aversion" effect emerging in contexts of excessive transparency has been already introduced in an efficiency wage model by Chang and Lai (1999), who assume that increasing workplace monitoring may undesirably reduce the worker's effort when the feeling of psychological deprivation it induces offsets the transparency gains from easing labour surveillance.

feel less intrinsically attached to their jobs – anecdotes indicate that workers use expressions such as "It's my baby" or "There's a bit of my blood in there" when speaking about their tasks (Reynolds, 1973). On the other hand, employees may perceive monitoring as a breach of the psychological contract they tacitly sign with their employers (Frey, 993a,b), feeling less morally obliged to reciprocate through higher labour effort.

Third, the mechanism we have in mind when we assume that DM increases average labour productivity is both realistic and grounded in previous research. Indeed, DM may help to provide real-time feedback on workers' performance and its alignment with the objectives of the firm without recurring to the subjective (potentially arbitrary) assessment of supervisors. In addition, DM may also allow managers to identify bottlenecks and anticipate demands in terms of workforce support, enabling better targeting of on-the-job training initiatives and recruitment and retention of talented workers (Aral et al., 2012; Adhvaryu et al., 2022).

Applying a tie-breaking rule whereby the employer implements the technology when indifferent between adopting ($D = 1$) and non-adopting ($D = 0$), the employer chooses $D = 1$ when $\Pi^*(1, E) - \Pi^*(0, E) \geq 0$, and $D = 0$ otherwise, where equilibrium profits $\Pi^*(D, E)$ are evaluated at the efficiency-wage level $w \equiv w^*(D, E)$ that elicits the employee's highest possible effort $e \equiv e^*(D, E)$ conditional on the employer's decision on D and on the presence of the employee organization E.

2.4 Employee representation

Among the four channels listed in the previous section, we assume that two are affected by the presence of a firm-level body of employee representation, as detailed in what follows.

(i) *Disciplining effect*—By limiting the extent to which the employer can use the technology to impose sanctions (e.g. dismissals) to underperforming workers, employee representation reduces the effective level of work transparency, so that $\mu(D) \equiv \mu(D, E)$ and $1 \geq \mu(1, 0) > \mu(1, 1) \geq \mu(0, E) > 0$.

(ii) *Commitment effect*—By making the workforce feel more involved in the process of technology adoption and voicing employees' discomfort with intrusive monitoring, the presence of employee representation reduces the sense of psychological deprivation that arise, for instance, from reduced task commitment or increased mistrust, so that $c(e,D) \equiv c(e,D,E)$ with $c(e,1,0) > c(e,1,1) \geq c(e,0,E) > 0 \forall e > 0$.

To focus on how employee representation may affect the willingness to invest in digital monitoring, we assume that the firm's economic performance does not depend on the voice ability of the organization when the digital monitoring tool is not introduced. This implies that firms are ex-ante identical vis-à-vis their investment decision; that the employer's fall-back profit does not depend on E, so that $\Pi^*(0,1) = \Pi^*(0,0)$, and consequently, that $\Pi^*(1,1) - \Pi^*(1,0) \geq 0$ is a sufficient condition for employee organizations to increase digital monitoring incentives.

2.5 Results

Although it would be possible to derive our main results using general functions, to focus on the economic intuitions and keep the mathematics simple we impose some restrictions upon the worker's output and effort cost functions. Since the worker's optimal choice is interior when $c(e)$ is quasi-convex and $\pi(e)$ quasi-concave (at least one strictly so), we assume – as standard in this type of contract-theoretic problems (e.g., Beckmann and Kräkel (2022)) – that $\pi(e) = \alpha e$ and $c(e) = \delta e^2/2$, where $\alpha \equiv \alpha(D) > 0$ and $\delta \equiv \delta(D,E) > 0$ are two shifters that model the productivity and commitment effects postulated above, so that $\alpha(1) > \alpha(0)$ and $\delta(1,0) > \delta(1,1)$. The following Lemma characterizes the employer's decision of w and the employee's decision of e.

Lemma 1—*In equilibrium, the efficiency-wage and the worker's effort are given, respectively, by*

$$w^*(D,E) = \frac{1}{2}\left[w_0 + \frac{\Delta}{\mu} - \frac{\delta(1-\mu)}{(\alpha\mu)^2}\right] \quad \textit{and} \quad e^*(D,E) = \frac{1}{2\delta}\left[\alpha(\Delta - \mu w_0) - \frac{\delta(1-\mu)}{\alpha\mu}\right]$$

Proof: see the Theoretical Appendix.

A quick inspection of the choice variables described in Lemma 1 reveals that it is ex-ante impossible to determine which effect the adoption of the digital monitoring technique exerts on the equilibrium effort and efficiency-wage, and that the possible moderating role played by the employee representation is just as ambiguous. Indeed, when the employer selects $D = 1$ instead of $D = 0$, work transparency improves – $\mu(1,E) - \mu(0,E) > 0$ – average labour productivity increases – $\alpha(1) - \alpha(0) > 0$ – but the employee's morale deteriorates – $\delta(1,E) - \delta(0,E) > 0$ – where the first and third effects are smaller when the employee organization is in place – $\mu(1,0) - \mu(1,1) > 0$ and $\delta(1,0) - \delta(1,1) > 0$. Given this, some terms in the expressions of w^* and e^* increase, some decrease, so that the total effect is not monotonic.

To analyze the employer's decision of D, assume that digital monitoring incentives always exist, so that $\Pi^*(1,E) - \Pi^*(0,E) \geq 0$. Given the facilitating assumption that $\Pi^*(0,0) = \Pi^*(0,1)$ (the employee organization has no effect on firm performance when DM remains unimplemented), a sufficient condition for employee organizations to incentivize investments in digital monitoring is $\Pi^*(1,1) - \Pi^*(1,0) \geq 0$. The following Lemma characterizes the effect of E on the employer's decision of D.

Lemma 2—*Defining $\omega(D,E) \equiv [1-\mu(1-e^*)]w^*$, the employee organization increases digital monitoring incentives iff $\Pi^*(1,1) - \Pi^*(1,0) \geq 0$, or, alternatively, iff*

$$(e^*(1,1) - e^*(1,0))\alpha\Delta \geq \omega(1,1) - \omega(1,0)$$

Proof: see the Theoretical Appendix.

While the term on the l.h.s. of the inequality in Lemma 2 measures the different effort response of an organized and non-organized worker after a DM-technology is adopted, that on its r.h.s. quantifies how the efficiency wage endogenously react to these different adjustments. Given the assumption that the employee organization may affect both changes either positively (by mitigating the adverse commitment effect arising from the worker's control aversion) or negatively (by limiting the extent to which the employer can actually rely on the DM-technology as a labor discipline device) whether employee organizations hinder or encourage digital monitoring incentives is ultimately an empirical question, to which we shall answer in the following section.

3 Data

3.1 The European Company Survey

We analyze the relationship between institutions of employee voice, more specifically employee representation (ER), and the adoption of digital-based monitoring technologies 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.[13] A crucial advantage of this survey is that it provides harmonized cross-country information on employee representation and utilization of advanced technologies. In addition, the survey reports rich details about management practices and organizational design at the workplace level.

A. Measure of shop-floor employee representation. Since our focus is on collective procedures to negotiate digitally enforced transparency, we consider in the analysis only institutionalized forms of employee representation. In particular, employee representation is a dummy variable identifying establishments with a trade union, works council or any other country-specific official structure of employee representation (e.g. joint consultative committees). This definition excludes ad-hoc forms of representation and individual employee voice mechanisms.

B. Measure of digital-based monitoring technologies. The survey provides information on establishment-level utilization of advanced monitoring technologies. Our measure is a dummy variable equal to 1 if the establishment actually uses digital-based monitoring, defined in the survey questionnaire as "data analytics to monitor employee performance". We also consider an additional indicator of whether the establishment has expanded the use of data analytics in the last three years.

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 the use of pay-for-performance compensation schemes. There is also information on the fraction of workers performing complex and non-routine tasks, i.e. *"jobs that require to find solutions to unfamiliar problems"*. This rich set of information allows to 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 27% of establishments report the use digital-based monitoring technologies. Figure 1 displays the share of establishments using digital-based monitoring devices by country and workplace ER status. In most cases, establishments with ER exhibit a higher average use of such technologies compared

[13]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.

to establishments without ER. Moreover, as shown in Figure 3, this difference tends to hold regardless of several establishment characteristics, including the competitiveness and the predictability of the market in which the firm operates. This reinforces our intuition that the factors driving the decision to expand work transparency through digital monitoring are at least partially internal, rather then just external, to the firm. Moreover, the more intensive use of digital-based monitoring technologies under worker voice arrangements holds independently of past and projected employment changes, i.e. for both growing and shirking establishments.

4 Results

4.1 Correlation between ER and digital-based monitoring technologies

We begin by considering the following regression model:

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

where subscripts i, j and c denote the establishment, industry and country, respectively; Y_{ijc} is a dummy variable equal to 1 if the establishment i in industry j and located in country c uses digital technologies to monitor employee performance, ER_{ijc} is a dummy variable for the presence of ER at the establishment level; $\mathbf{X}_{ijc}$ is the vector of controls; ε_{ijc} are the residuals.

Table 2 shows the results from estimating a series of Linear Probability Models where the dependent variable is the use of digital-based monitoring. In column (1), we estimate a parsimonious model in which we only include a dummy variable that takes value 1 for establishments in which there is an ER body in place and a full set of industry and country dummies. The presence of ER is positively associated with the probability of using digital-based monitoring technologies at the workplace level. In columns (2) to (5), we sequentially add more controls to see the robustness of the results. In column (2), estimates control for establishment-level differences, including a dummy variable identifying multi-site firms, the age of the establishment, 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 controls for 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. According to our preferred estimates reported in column (5), the presence of ER is associated with 3.6 percentage point increase in the use of digital technologies to monitor employee performance.[14]

We also consider information about changes in the utilization of digital monitoring technologies in the last three years at the establishment level. We estimate an Ordered Probit Model in which the dependent variable is categorical and takes value 0 if the establishment does make any use of AI-based technologies (data analytics) for the purpose of improving production processes and monitoring production and employee performance, 1 if the establishment currently uses digital monitoring technologies but utilization decreased or remained stable in the last three years, and 2 if the establishment utilizes digital monitoring and expanded its use. Results reported in Table 3 indicate that the presence of ER is significantly associated with an expanding use of digital monitoring technologies. According to the average marginal effects estimates reported in Table 4, the probability of not using any AI-based technology is 4 percentage points lower in establishments with ER compared to establishments without ER bodies. On the contrary, establishments with ER bodies are 1 percentage point more likely than establishments without ER to use digital monitoring with stable/declining utilization in the last three years, and about 3 percentage points more likely to use digital monitoring technologies with expanding utilization. Therefore, conferring negotiation rights over the implementation of workplace digital monitoring to employee representatives does not appear to hinder the utilization of these technologies. If anything, there is evidence of a positive association between digital monitoring and worker voice institutions at both the extensive and intensive margins.[15]

[14] We perform a series a robustness checks, obtaining qualitatively similar results. First, we estimate average marginal effects using Probit models. Second, we add additional controls for investments in customised software and the use of different forms of variable pay (e.g. profit sharing) that may complement the utilization of digital-monitoring technologies (Aral et al., 2012). Third, we perform additional estimates restricting the sample to countries where national legislation confers special rights to ER bodies in relation to the use of digital-based monitoring technologies (Eurofound, 2020). Finally, we report additional estimates in which we unpack the effect of different types of ER bodies (unions, works councils and other types of ER). Interestingly, the positive correlation between ER and DMT holds regardless of ER type. Results are reported in Appendix Table A1.

[15] One could argue that the presence of ER may induce more adversarial labour-management rela-

4.2 Mechanisms

Having shown a positive correlation between ER and the use of DMT, we now explore the empirical plausibility of the two main channels highlighted by the theoretical framework developed in Section 2.

Firstly, we exploit rich information reported by managers on the *de facto* influence exerted by employee representatives in relation to important decision areas of management in the last three years. These areas include (i) dismissals, (ii) training, (iii) work organization, (iv) working time management and (v) variable pay. Apart from the information on the strength of ER influence, managers also indicate if no decisions were actually made on a given subject matter. This allows us to extend the analysis beyond the crude ER dummy, opening the black box of ER activity within establishments and assessing its correlation with DMT along the intensive margin. The results of this empirical exercise are reported in Table 5. Overall, we find that the likelihood of using DMT is higher in establishments in which ER exerts a certain degree of influence on management decisions relative to establishments without ER bodies. This additional result is reassuring as shows that the positive correlation between ER and DMT is driven by establishments in which ER is actually active and influential as perceived by managers.[16] Moreover, we find that the greater the influence of ER bodies in certain decision areas, the higher the probability of using DMT. In other words, the probability of using DMT is significantly higher in establishments in which ER has moderate to great power than in establishments in which ER has small or no power. Interestingly, this only holds for managerial decisions related to training, work organization and working time management, suggesting that the presence of ER may enhance the complementarity between work systems and DMT.

The correlation of ER influence on dismissals decisions and DMT is of particular interest as it speaks to one of the channels highlighted by our theoretical model. Data

tions. Employers may respond to the presence of ER by adopting DM technologies in order to maintain control. To check for this alternative explanation, we estimate equation (1) while controlling for the occurrence of industrial actions in the last three years (strikes, work-to-rule, or manifestations) and managers' perceptions on bad workplace climate. If digital monitoring is driven by employers' need to maintain control in establishments with ER characterized by a more conflicting work environment, the additional controls should pick up the effect of ER. Results report in Appendix Table A1 indicate that the effect of ER remains positive and significant even when controlling for proxies of labour-management conflict.

[16] Indeed, we observe that the effect of passive ER presence (i.e. cases where no decision was made on a specific managerial domain) is not significantly different from the case where ER is absent.

on worker activity generated by DMT facilitates workplace surveillance and enhance the credibility of dismissal threats, inducing the extraction of more effort. Hence, one implication of the model is that ER involvement in dismissals decisions may undermine the disciplining effect of DMT, reducing employers' incentives to invest in DMT. However, results report in column (1) of Table 5 suggest that this is not the case: ER involvement in dismissal procedures is positively associated with the utilization of DMT. In contrast to other management areas, however, there are no significant differences between establishments in which managers perceive ER has moderate to great ability to influence dismissals decisions relative to establishments in which ER has little or no power to do so.

Secondly, we turn to analyse whether the presence of ER bodies mitigates potential adverse commitment effects of DMT. According to our framework, the presence of ER allows workers to have a voice on how DMT are implemented in the workplace. The behavioural literature on control aversion suggests that detrimental performance responses to monitoring are more likely to be observed in production settings characterized by the prevalence of intrinsic motivations and task complexity (Falk and Kosfeld, 2006; Herz and Zihlmann, 2021). Therefore, we expect ER to facilitate the utilization of DMT precisely in such environments. As a proxy of the relative importance of intrinsic rewards, we use a survey question in which managers indicate how often the following practices are used to motivate and retain employees at their establishments: (i) communicating a strong mission, (ii) providing interesting and stimulating work, (iii) providing opportunities for training and development. As a proxy of task complexity, we use a categorical variable indicating the share of workers performing jobs that require finding solutions to unfamiliar problems.

We estimate equation (1) including interactions between these measures and ER presence. Results are reported in Table 6. We report the marginal effect of ER on the utilization of DMT (setting all the covariates to the mean), which is always positive and significant.[17] In columns 1-3, we report the results for different measures of intrinsic rewards. The effect of ER on the utilization of DMT is not significantly different for establishments using intrinsic rewards relatively more often than other establish-

[17] It is worth noticing that the coefficient associated with ER does not have the same interpretation as in the model with no interactions reported in Table 2. In this case, it represents the effect of ER when measures of intrinsic rewards and task complexity are held constant at the reference category, i.e. when these workplace practices are not used at all.

ments. In column 4 of Table 6, we present the results for task complexity. Interestingly, the presence of ER bodies is associated with a significantly greater utilization of DMT in establishments with a higher share of workers performing complex tasks (very frequent practice) compared to those in which complex tasks are not used. In Figure 3 (panel D), we plot the marginal effect of ER for establishments in which complex task are never used and establishments in which those tasks are very frequent. Indeed, the line for the group of establishments intensive in complex tasks looks steeper than the line for the other group, confirming that ER induces greater use of DMT in those production settings.

This result seems to be consistent with the idea that preserving zones of privacy around workers' activities is necessary to foster organizational learning and improve performance, particularly in production settings that require experimentation and innovative problem solving (Bernstein, 2012). Therefore, ER facilitates the use of DM technologies precisely in production settings where previous studies proved control-averse responses to monitoring to be more common. By enforcing procedural safeguards regarding the use of these technologies in the workplace, ER bodies may attenuate workers' negative commitment effects. The fact that the correlation between ER and DMT is stronger for establishments in which ER has greater decisional power in relation to training, work organization and working time, as documented in Table 5, suggests that ER may also attenuate negative responses to monitoring by influencing workplace practices that affect employee wellbeing and potentially complement DM technologies.

4.3 Size-Contingent Regulations: Local Randomization RD analysis

One obvious concern is that unobserved omitted variables may be driving the correlation between ER bodies and the use of digital-based monitoring technologies. As a complementary exercise, we use a regression discontinuity design (RDD) exploiting size-contingent regulations governing the operation of ER at the workplace level in most EU countries.[18] We expect these workplace size thresholds provide some exogenous variation in the presence of employee representation, mitigating concerns about

[18]In Appendix Table A2, we provide detailed information on ER rules by country. To construct this table, we use information from CBR-LRI (labor regulation) database (Adams et al., 2017) complemented by information on national industrial systems collected by ETUI (www.worker-participation.eu/) (see Fulton, 2020).

the endogenous formation of ER bodies (see Belloc et al. (2023) for a similar approach). 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 ($c = 0$).

While size cutoffs do not perfectly determine treatment (ER presence), as they allow employee representation to be established only if requested by employees, they may 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.[19]

Limitations. There are some 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 digital-based monitoring technologies contemporaneously. This raises concerns about potential feedback loops between processes involving the determination of firm size, the presence of ER bodies and the use of monitoring technology. Second, conducting the RDD analysis using workplace-data from many different countries involves the harmonization of complex legal rules regarding the precise conditions under which workers can trigger representation rights locally. 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 hard 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 it more difficult to observe a discontinuity in ER presence at the cutoff.

Specification and results. Given the fact that our forcing variable (establishment

[19]We also exclude observations from Malta and Cyprus due to low number of cases.

size) is discrete and has few mass points (i.e. values of the variable that are shared by many units) in its support[20], 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).[21]

An important procedural step is to select the window around the establishment 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.[22] In Table 7, 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. Figure 4 (Panel A) shows evidence of a discontinuity in the presence of ER at the cutoff point. In column (1) of Table 8, 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. 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 digital-based monitoring technologies. In column (2) of Table 8, we report a statistically significant difference of 4.6 percentage points in the use of digital technologies to monitor employee performance. This is also consistent with graphical evidence reported in Figure 3 (Panel B). Finally, in column (3) we show that there is a significant increase in the likelihood that the establishment expanded the utilization of digital monitoring in the last three years.[23] As shown in Panel B of Table 8, broadly

[20] We count 15900 observations with non-missing values of the forcing variable. However, the variable is discrete and has mass points, with 684 unique values. This would be the effective number of observations used in continuity-based RDD methods.

[21] For practical implementation, we use the functions *rdwinselect* and *rdrandinf*, part of the the *rdlocrand* package developed by Cattaneo et al. (2015).

[22] 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.

[23] This variable is defined on a 0-2 scale, as explained in the notes of Table 3 (0 = No use of AI-based technologies; 1 = Use of digital monitoring remained stable or decreased; 3 = Use of digital monitoring increased).

similar results are obtained when the analysis is restricted to single-site firms. We find positive albeit imprecisely estimated effects (p-value 0.122) on the use of digital-based monitoring technologies and positive and statistically significant effects on the expanding use of these technologies in the last three years.

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 Appendix Table A3 and Figure A1. 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 (Garicano et al., 2016; Aghion et al., 2021; Askenazy et al., 2022). The p-value of a binomial test is 0.158, indicating that there is no evidence of 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=15, 20, 25, 30, finding no evidence of treatment effects (see Appendix Table A4).

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 windows 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. In Appendix Table A5 we present the results from this exercise. Overall, the main findings hold for both smaller and larger windows. The only exception refers to the effect on digital monitoring, which appears to be statistically insignificant in smaller windows. This may relate to the fact that our RDD analysis is restricted to relatively small workplaces.

Summary. Overall, the results of the correlational and RDD analysis suggest the existence of a positive relationship between the presence of institutions granting employee voice and the use of technologies fostering digital transparency at work. Thus, far from discouraging digital monitoring, the existence of collective bodies that enjoy negotiation rights over the introduction of digital surveillance devices tends to induce firms to exert such monitoring to a greater extent. In our theoretical framework, this result can be rationalized by the fact that employee representation allows the workers and the employer to agree on a "fair monitoring" norm, which contributes to attenuate mis-behaviours associated with control aversion and hiding practices.

5 Conclusions

Our study analyzes the interplay between employee representation bodies and the utilization of digital-based monitoring technologies at the workplace level. Using establishment-level data from 28 European countries, we document a positive correlation between shop-floor employee representation and the utilization of data analytics to monitor employee performance. We obtain qualitatively similar results in a regression discontinuity framework in which we exploit variation created by country-specific size-contingent rules regulating the operation of ER bodies.

The utilization of new digital monitoring technologies may have different impacts for firms, workers and social welfare. On the one hand, they may improve the accuracy of information about the production process, improving information flows, enhancing operational learning and firm performance. On the other hand, employers' unlimited ability to monitor employee activities may have potentially harmful effects for workers' dignity, right to privacy and well-being, and reduce performance in certain settings. Importantly, profit-maximizing firms concentrating decisional power over the utilization of these technologies are ill-suited for internalizing some of these negative side effects. From a social point of view, it is not trivial how to aggregate these potential gains and losses from the implementation of digital monitoring, suggesting the need for greater democratic accountability when it comes to the use of these technologies (Kasy, 2023; Rogers, 2023). While there is some evidence on the mutually reinforcing relationship between artificial intelligence developments and autocrats' political control (Beraja et al., 2023), less attention has been devoted to the use of surveillance technologies in the relatively undemocratic context of most private business organizations (Dahl, 1985; Bowles and Gintis, 1993). Our study shows that restricting employers' discretion to use digital monitoring by conferring worker voice institutions an oversight and audit function in relation to these technologies does not seem to reduce the pace of technology adoption.

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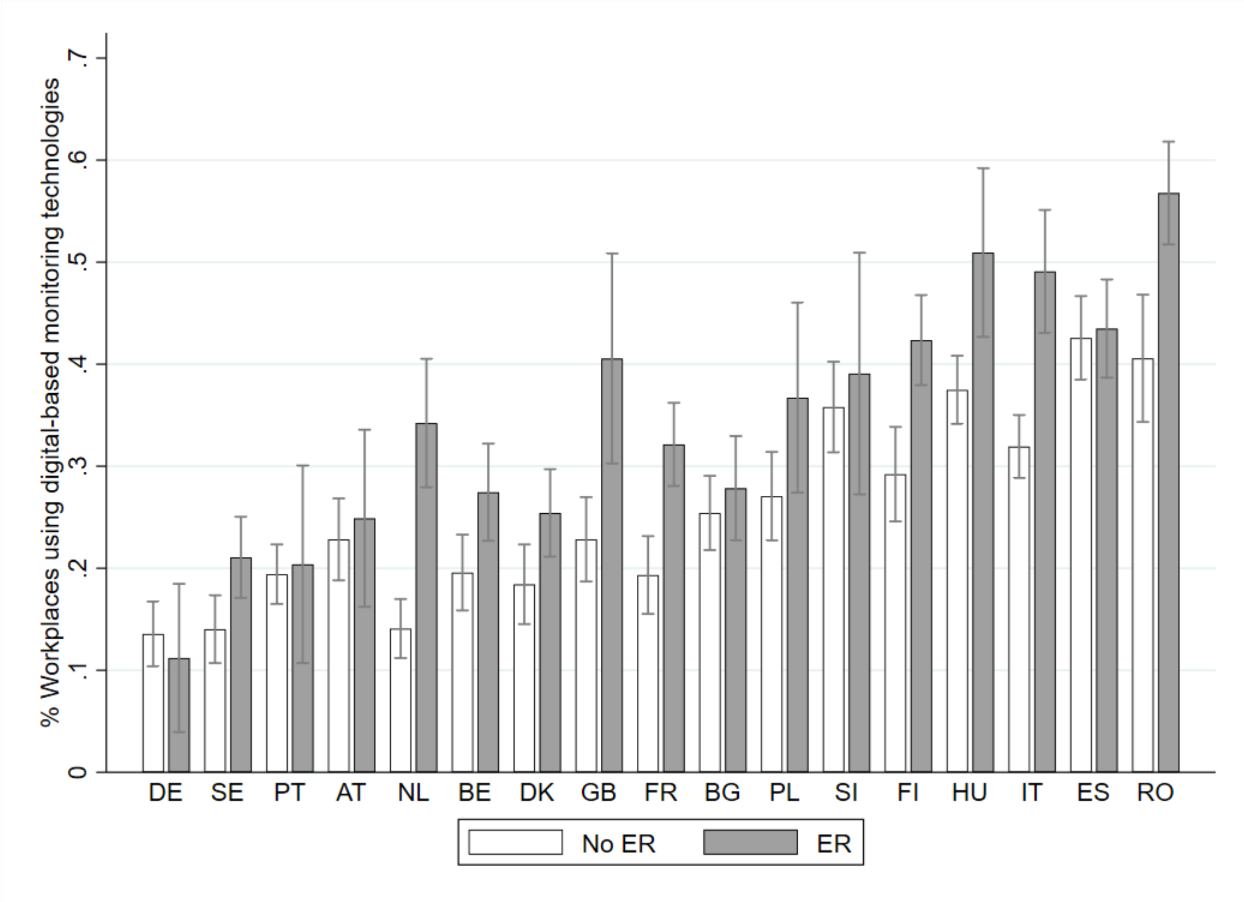
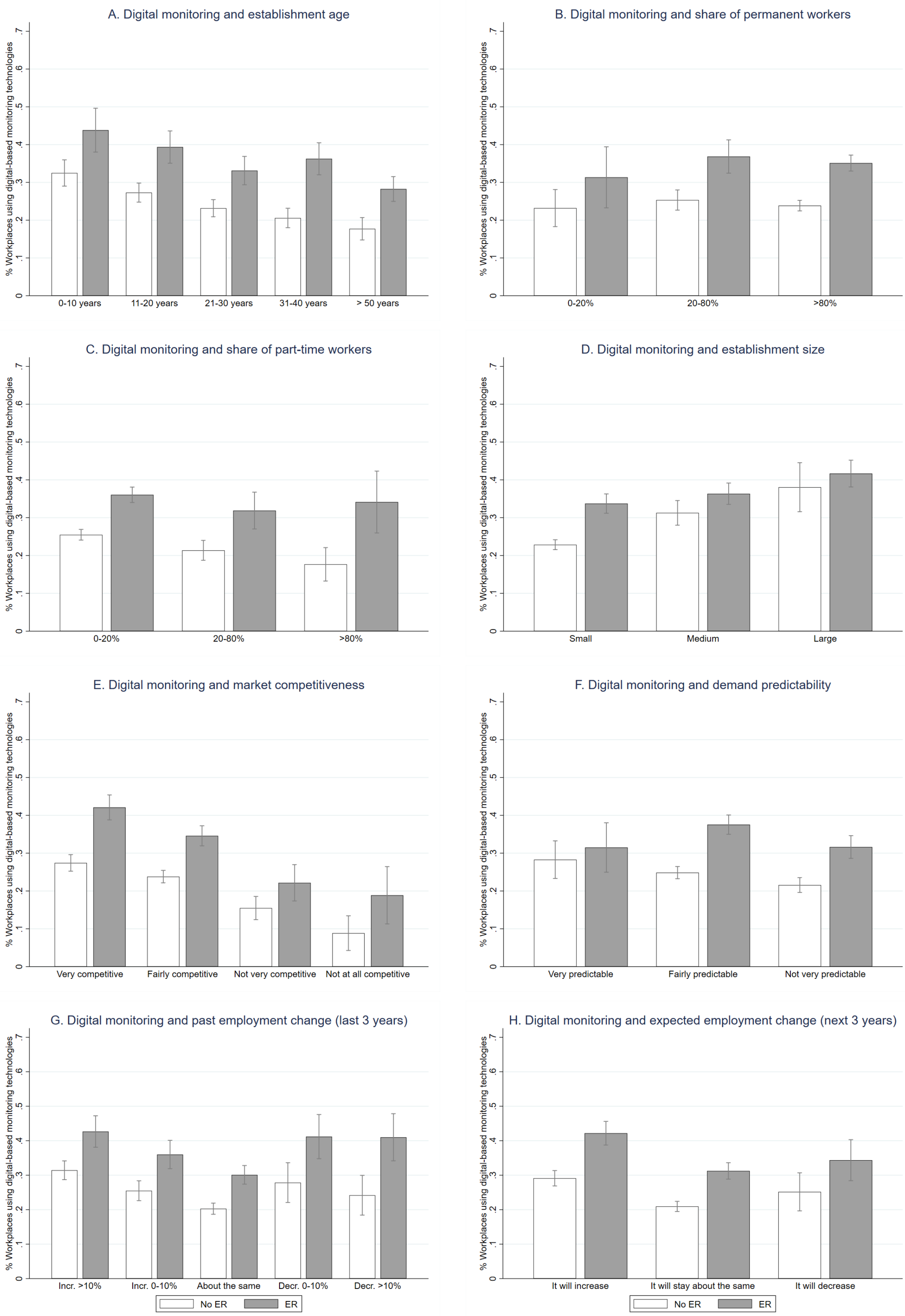
Figures and tables

Figure 1: Utilization of digital monitoring by workplace ER status in selected countries.



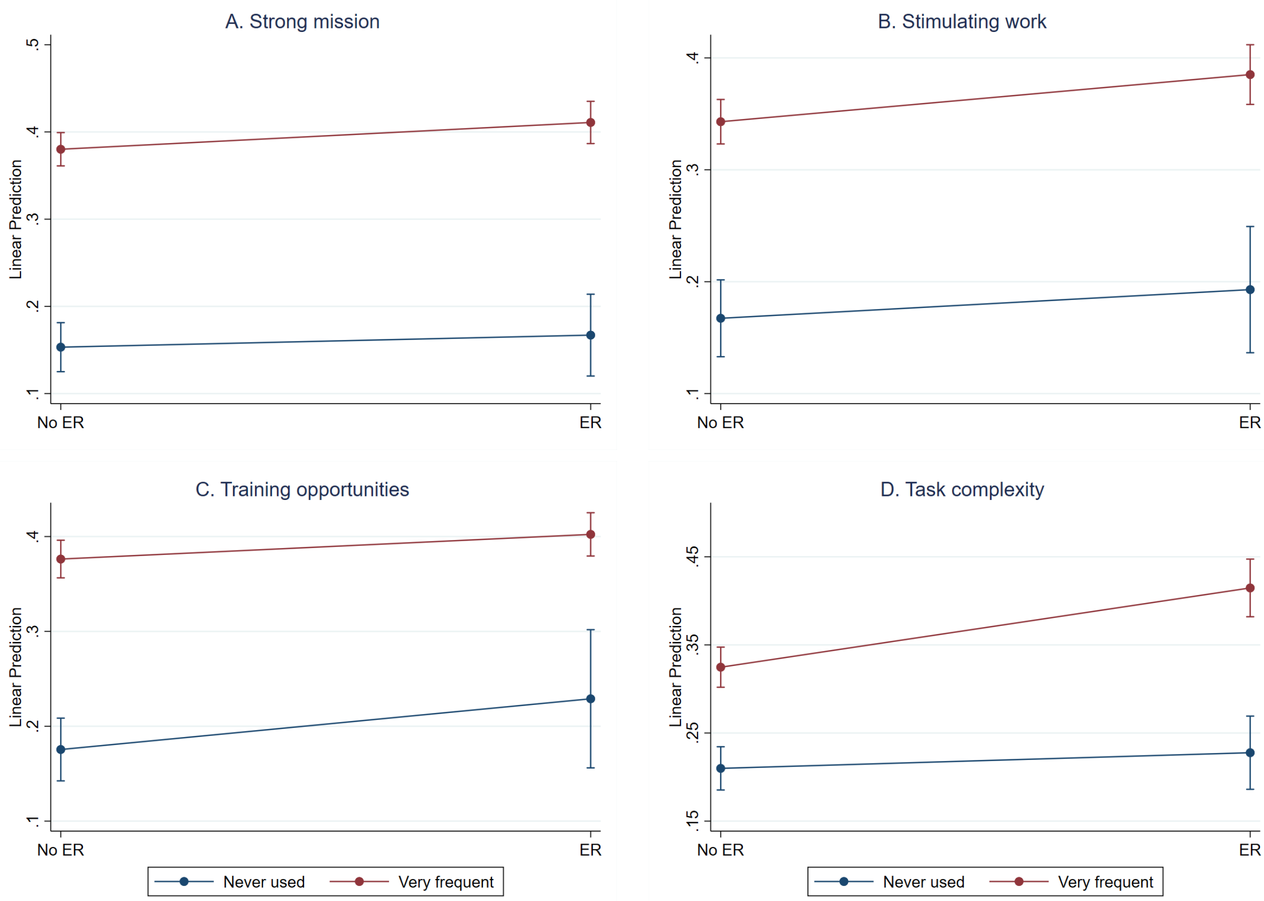
Notes: Pooled data from the European Company Survey 2019 (selected countries). Sample weights are used. The use of digital-based monitoring technologies refers to establishments using "use data analytics to monitor employee performance".

Figure 2: Digital monitoring and workplace characteristics.



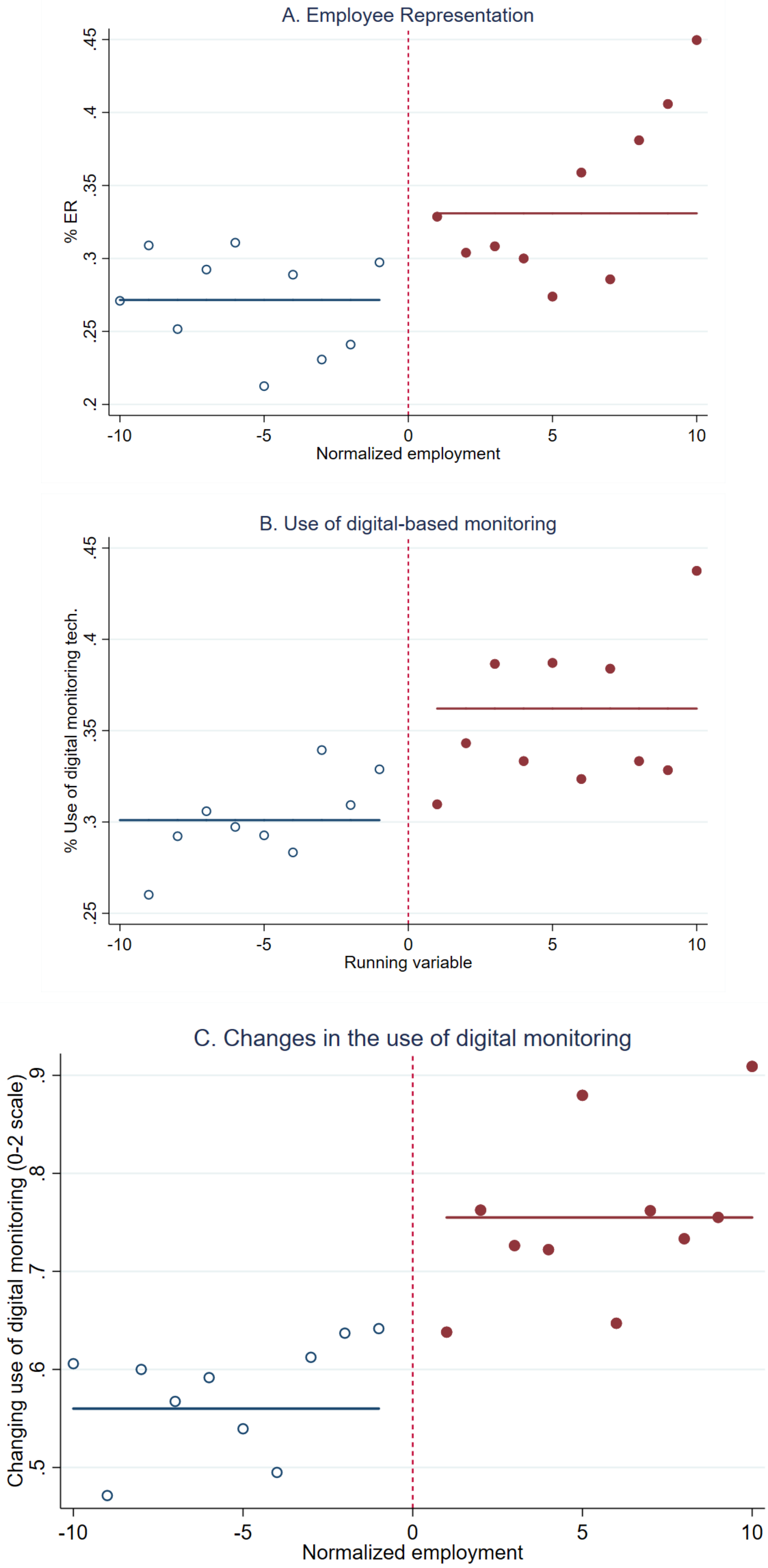
Notes: Pooled data from the European Company Survey 2019. Sample weights are used. The use of digital-based monitoring technologies refers to establishments using "use data analytics to monitor employee performance".

Figure 3: Correlation between ER and Digital monitoring: role of intrinsic rewards and task complexity



Notes: Plot of marginal effect of ER bodies on DMT. Communicating a strong mission, stimulating work and training opportunities are coded as infrequent practices if they are offered not very often, as frequent practices if offered often, and as very frequent practices if offered very often. Dealing with complex tasks is coded as an infrequent practice if less than 20% of the workers deal with unfamiliar problems, as a frequent practice if 20% to 80% of the workers deal with unfamiliar problems, and as a very frequent practice if more than 80% of the workers deal with unfamiliar problems. For all practices, the benchmark category is never using the given practice. 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.

Figure 4: RD plots: ER and digital-based monitoring.



Notes: *rdplots* of the incidence of employee representation (panel A), current use of digital monitoring (panel B) and changes in the use of digital monitoring (0-2 scale) as defined in Table 3 (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 [-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 body currently exists in the establishment (yes/no)	0.247	0.432
Digital monitoring (current use)	Data analytics to monitor employee performance (yes/no)	0.267	0.4443
Digital monitoring (changes)	Changes in the last three years (0 = No use; 1 = Use of digital monitoring remained stable or decreased; 3 = Use of digital monitoring increased)	0.550	0.804
Process innovation	Establishment introduced new or significantly changed processes (yes/no)	0.291	0.454
Product innovation	Establishment introduced new or significantly changed products or services (yes/no)	0.319	0.466
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
% Non-routine tasks	% employees whose job involves finding solutions to unfamiliar problems $>$ 40%	0.363	0.481
% Permanent workers	% employees in the establishment with an open-ended contract $>$ 80%	0.760	0.427
% Part-time workers	% employees in the establishment working part-time are $>$ 80%	0.054	0.225
% High market competition	The market for the main product/service is very competitive (yes/no)	0.355	0.478
% High market uncertainty	The market for the main product/service is not predictable at all (yes/no)	0.077	0.267
% Female manager	The manager answering to the questionnaire is a woman	0.519	0.500
% Owner-manager	Position held by the manager: owner-manager (yes/no)	0.205	0.404

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

Table 2: Current use of digital-based monitoring technologies and ER.

	(1)	(2)	(3)	(4)	(5)
ER	0.091***	0.034***	0.034***	0.038***	0.036***
	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)
Observations	21,772	21,499	21,019	20,574	20,502
R-squared	0.074	0.092	0.092	0.100	0.102
Country + industry dummies	Yes	Yes	Yes	Yes	Yes
Establishment-level controls	No	Yes	Yes	Yes	Yes
Workforce composition	No	No	Yes	Yes	Yes
Competitive/Uncertain environment	No	No	No	Yes	Yes
Manager's controls	No	No	No	No	Yes

Notes: Notes: Estimates obtained from LPM models with robust standard errors in parentheses. The dependent variable is a dummy variable indicating whether the establishment uses use data analytics to monitor employee performance. 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: Changes in the use of digital-based monitoring technologies and ER: Ordered probit estimates.

	(1)	(2)	(3)	(4)	(5)
ER	0.371***	0.116***	0.114***	0.128***	0.121***
	(0.022)	(0.025)	(0.025)	(0.025)	(0.025)
Observations	16,530	16,339	15,961	15,642	15,590
Country + industry dummies	Yes	Yes	Yes	Yes	Yes
Establishment-level controls	No	Yes	Yes	Yes	Yes
Workforce composition	No	No	Yes	Yes	Yes
Competitive/Uncertain environment	No	No	No	Yes	Yes
Manager's controls	No	No	No	No	Yes

Notes: Notes: Estimates obtained from Ordered Probit Models with robust standard errors in parentheses. The dependent variable is a categorical variable and takes value 0 if the establishment does not make any use of AI tools for the purpose of monitoring production and employee performance, 1 if the establishment currently uses digital monitoring technologies but utilization decreased or remained stable in the last three years, and 2 if the establishment utilizes digital monitoring and expanded its use in 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: Changes in the use of digital-based monitoring technologies and ER: Ordered probit estimates (marginal effects).

	(1) No use of AI technologies	(2) Use of digital monitoring decreased or remained stable	(3) Use of digital monitoring increased
ER	-0.041***	0.009***	0.032***
	(0.009)	(0.002)	(0.007)
Observations	15,590	15,590	15,590
Country + industry dummies	Yes	Yes	Yes
Establishment-level controls	Yes	Yes	Yes
Workforce composition	Yes	Yes	Yes
Competitive/Uncertain environment	Yes	Yes	Yes
Manager's controls	Yes	Yes	Yes

Notes: Notes: Marginal effects corresponding to Ordered Probit estimates reported in column (5) of Table 3. The dependent variable is a categorical variable and takes value 0 if the establishment does not make any use of AI tools for the purpose of monitoring production and employee performance, 1 if the establishment currently uses digital monitoring technologies but utilization decreased or remained stable in the last three years, and 2 if the establishment utilizes digital monitoring and expanded its use in 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 5: Mechanisms: Current use of digital-based monitoring technologies and ER influence in given decision areas.

	(1)	(2)	(3)	(4)	(5)
(1) ER is present but no decisions were made	0.020*	0.016	0.009	0.006	0.009
	(0.012)	(0.016)	(0.017)	(0.014)	(0.013)
(2) ER influence was small or nonexistent	0.037***	0.019***	0.025***	0.027***	0.036***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
(3) ER influence was moderate or great	0.056***	0.064***	0.056***	0.062***	0.055***
	(0.014)	(0.010)	(0.010)	(0.010)	(0.012)
Decision area	Dismissals	Training	Work organization	Working time management	Variable pay
Test of group differences:					
(2) vs (1)	0.017	0.004	0.017	0.022	0.027
	[-0.008, 0.042]	[-0.031, 0.039]	[-0.019, 0.053]	[-0.009, 0.052]	[-0.002, 0.055]
(3) vs (2)	0.019	0.044	0.030	0.034	0.019
	[-0.011, 0.048]	[0.022, 0.067]	[0.008, 0.052]	[0.011, 0.057]	[-0.006, 0.044]
Observations	20,502	20,502	20,502	20,502	20,502
R-squared	0.101	0.102	0.101	0.101	0.101
Country + industry dummies	Yes	Yes	Yes	Yes	Yes
Establishment-level controls	Yes	Yes	Yes	Yes	Yes
Workforce composition	Yes	Yes	Yes	Yes	Yes
Competitive/Uncertain environment	Yes	Yes	Yes	Yes	Yes
Manager's controls	Yes	Yes	Yes	Yes	Yes

Notes: Notes: Estimates obtained from LPM models with robust standard errors in parentheses. The dependent variable is a dummy variable indicating whether the establishment uses use data analytics to monitor employee performance. With respect to ER involvement in given decision areas, the benchmark category is ER absence. Contrast of group differences with 95% confidence intervals in square brackets. 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: Mechanisms: Current use of digital-based monitoring technologies and ER where intrinsic motivations and task complexity are important.

	(1)	(2)	(3)	(4)
ER	0.014	0.021	0.048	0.016
	(0.027)	(0.033)	(0.040)	(0.024)
Infrequent practice	0.100***	0.098***	0.081***	0.052***
	(0.015)	(0.018)	(0.017)	(0.014)
Frequent practice	0.165***	0.149***	0.154***	0.099***
	(0.015)	(0.018)	(0.017)	(0.013)
Very frequent practice	0.229***	0.114***	0.202***	0.062***
	(0.017)	(0.020)	(0.019)	(0.017)
ER × infrequent practice	0.021	0.012	-0.023	0.032
	(0.029)	(0.035)	(0.042)	(0.026)
ER × frequent practice	0.017	0.016	-0.015	-0.002
	(0.029)	(0.034)	(0.041)	(0.026)
ER × very frequent practice	0.016	0.021	-0.022	0.073**
	(0.031)	(0.037)	(0.043)	(0.031)
Practice	Communicating a strong mission	Providing stimulating work	Providing training opportunities	Dealing with complex tasks
Marginal effect of ER	0.033	0.036	0.030	0.036
	[0.000]	[0.000]	[0.000]	[0.000]
Observations	20,370	20,364	20,413	20,056
R-squared	0.113	0.107	0.111	0.106
Country + industry dummies	Yes	Yes	Yes	Yes
Establishment-level controls	Yes	Yes	Yes	Yes
Workforce composition	Yes	Yes	Yes	Yes
Competitive/Uncertain env.	Yes	Yes	Yes	Yes
Manager's controls	Yes	Yes	Yes	Yes

Notes: Notes: Estimates obtained from LPM models with robust standard errors in parentheses. The dependent variable is a dummy variable indicating whether the establishment uses use data analytics to monitor employee performance. Communicating a strong mission, stimulating work and training opportunities are coded as infrequent practices if they are offered not very often, as frequent practices if offered often, and as very frequent practices if offered very often. Dealing with complex tasks is coded as an infrequent practice if less than 20% of the workers deal with unfamiliar problems, as a frequent practice if 20% to 80% of the workers deal with unfamiliar problems, and as a very frequent practice if more than 80% of the workers deal with unfamiliar problems. For all practices, the benchmark category is never using the given practice. 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. Marginal effects of ER with all covariates set to the mean (p-value reported in square bracket). *** p<0.01, ** p<0.05, * p<0.1.

Table 7: 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: 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 8: Randomization-based approach: main results.

	ER	Digital monitoring	Changes in the use of digital monitoring (0-2 scale)
A. All establishments			
Point estimate	0.046	0.046	0.157
p-value	0.036	0.029	0.000
Window	[-4 4]	[-4 4]	[-4 4]
Sample size treated	935	930	794
Sample size control	998	997	713
B. Single-site firms			
Point estimate	0.047	0.038	0.152
p-value	0.025	0.122	0.003
Window	[-4 4]	[-4 4]	[-4 4]
Sample size treated	730	726	558
Sample size control	776	775	622

Notes: Table reports the results from the RDD estimation for the incidence of employee representation (Column 1), current use of digital monitoring (Column 2) and changes in the use of digital monitoring (0-2 scale) as defined in Table 3 (column 3).. 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).

Online Appendix

A Supplementary Tables and Figures

Table A1: Current use of digital-based monitoring technologies and ER: Robustness checks.

	(1)[a]	(2)[b]	(3)[c]	(4)[d]	(5)[e]	(6)[f]
ER	0.041***	0.114***	0.039***	0.060***		0.036***
	(0.013)	(0.024)	(0.008)	(0.015)		(0.008)
Customised software inv.			0.094***			
			(0.006)			
Profit sharing is used			0.059***			
			(0.007)			
Ind. action in the last 3yrs						0.046*
						(0.023)
Bad work climate						-0.027***
						(0.008)
ER type: Unions					0.029***	
					(0.010)	
ER type: Works councils					0.032***	
					(0.011)	
ER type: Other					0.051***	
					(0.013)	
Observations	6,987	20,502	18,271	4,774	20,502	20,502
R-squared	0.109	0.086	0.116	0.128	0.102	0.102
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 env.	Yes	Yes	Yes	Yes	Yes	Yes
Manager's controls	Yes	Yes	Yes	Yes	Yes	Yes

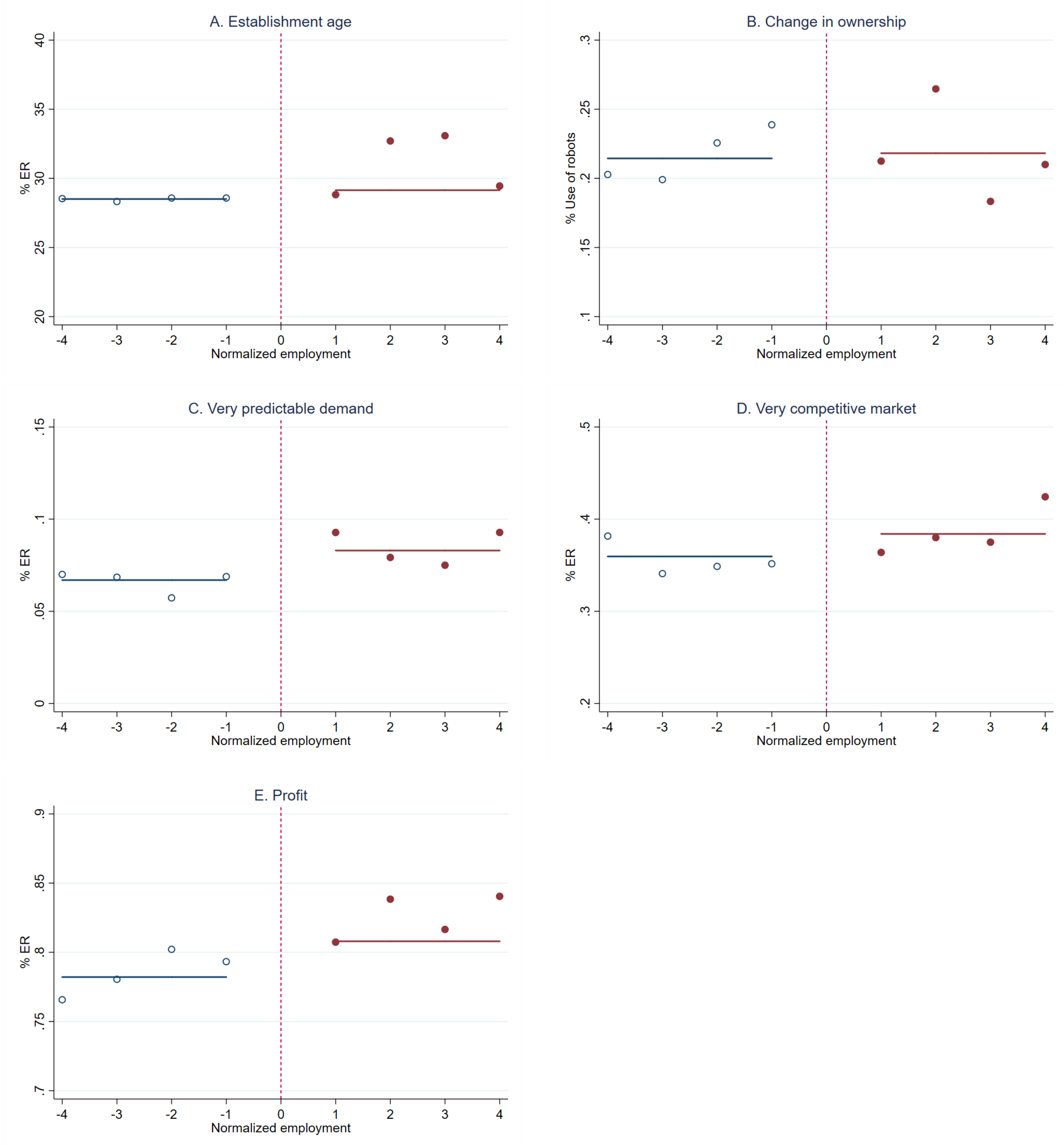
Notes: The dependent variable is a dummy variable indicating whether the establishment uses use data analytics to monitor employee performance. Establishment-level controls: plant size, plant age, multi-site, change in ownership. Workforce composition: % permanent contracts, % part-time workers. Competitive/uncertain environment: predictability of demand and competitive pressures as perceived by the manager. Manager's controls: gender and position. [a] LPM, sample w/out establishment with firm-level wage collective agreements; [b] Probit estimates (marginal effects are reported, R-squared is pseudo R-squared), whole sample; [c] LPM, whole sample; [d] LPM, sample restricted to countries w/ special rights conferred to ER bodies in relation to the use of digital-based monitoring technologies; [e] LPM, whole sample, types of ER are unpacked; [f] LPM, whole sample. *** p<0.01, ** p<0.05, * p<0.1.

Table A2: 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.

Figure A1: 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 A3: 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 A4: Placebo cutoff size thresholds.

	ER	Digital monitoring	Changes in the use of digital monitoring (0-2 scale)
c=15			
Point estimate	0.017	0.012	0.065
p-value	0.659	0.786	0.385
Sample size treated	406	404	301
Sample size control	384	382	294
c=20			
Point estimate	0.039	-0.018	-0.016
p-value	0.317	0.634	0.857
Sample size treated	391	391	293
Sample size control	311	310	238
c=25			
Point estimate	-0.015	0.030	0.024
p-value	0.716	0.503	0.779
Sample size treated	287	286	114
Sample size control	266	266	98
c=30			
Point estimate	-0.059	0.056	0.059
p-value	0.189	0.201	0.578
Sample size treated	327	325	233
Sample size control	217	216	143

Notes: Table reports results from RDD estimates using fake cutoff size thresholds (c=15, 20, 25, 30). 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).

Table A5: Sensitivity of randomization-based RD results: ER and automation technologies for different window choices.

	ER	Digital monitoring	Changes in the use of digital monitoring (0-2 scale)
[-3 3]			
Point estimate	0.059	0.033	0.108
p-value	0.012	0.217	0.031
Sample size treated	835	831	641
Sample size control	638	637	497
[-5 5]			
Point estimate	0.053	0.054	0.185
p-value	0.003	0.007	0.000
Sample size treated	1,092	1,085	821
Sample size control	1,285	1,284	1,022
[-11 11]			
Point estimate	0.077	0.064	0.199
p-value	0.000	0.000	0.000
Sample size treated	1,872	1,862	1,416
Sample size control	2,366	2,362	1,893
[-15 15]			
Point estimate	0.067	0.071	0.205
p-value	0.000	0.000	0.000
Sample size treated	2,135	2,122	1,606
Sample size control	2,831	2,826	2,241

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).

B Theoretical Appendix

B.1 Proof of Lemma 1

As usual, we solve the game by backward induction, starting from the employee's decision of $e \geq 0$ at stage 2 and moving to the employers' decision of $w > 0$ and $D \in \{0,1\}$ – conditional on $E \in \{0,1\}$ – at stage 1. Under the assumptions $\pi(e) = \alpha e$ and $c(e) = \delta e^2/2$, the worker's problem is given by

$$\max_e U(e) = \alpha e w + (1-\alpha e)[\mu w_0 + (1-\mu)w] - \frac{\delta}{2}e^2$$

the solution of which gives the best-response schedule

$$e(w) = \frac{\alpha\mu(w-w_0)}{\delta}$$

that can be rearranged to the following incentive compatibility constraint for the employer

$$e(w) = w_0 + \frac{\delta}{\alpha\mu}e$$

whose efficiency-wage problem at stage 1 is given by

$$\max_w \Pi(w) = \alpha e(w)(y_H - w) + (1-\alpha e(w))[\mu y_L + (1-\mu)(y_H - w)] - k$$

that, using the incentive compatibility constraint derived above and the fact that$\Delta \equiv y_H - y_L$, can be rearranged to

$$\max_w \Pi(w) = y_L - (1-\mu)w_0 - k + \left[\alpha(\Delta - \mu w_0) - \frac{\delta(1-\mu)}{\alpha\mu}e\right] - \delta e^2$$

subject to the employee's participation constraint

$$\alpha e w + (1-\alpha e)[\mu w_0 + (1-\mu)w] - \frac{\delta}{2}e^2 \geq w_0$$

that, using again the participation constraint, simplifies to

$$\delta e \left[\frac{\delta(1-\mu)}{\alpha\mu} + \frac{1}{2}e \right] \geq 0$$

which is always satisfied, so that the employer's decision of w is obtained by solving

$$\frac{\partial \Pi}{\partial w} \equiv \left[\alpha(\Delta - \mu w_0) - \frac{\delta(1-\mu)}{\alpha\mu} - 2\delta e \right] \frac{\partial e}{\partial w}$$

for e, obtaining the equilibrium effort described in Lemma 1, which can be inserted in the employee's participation constraint to obtain the efficiency wage described in Lemma 1 ■

B.2 Proof of Lemma 1

The maximized value of the employer's objective function conditional on D and E once the equilibrium effort and efficiency wage have been determined is given by

$$\Pi^*(D, E) = y_L + \alpha e^* \Delta - [1 - \mu(1 - e^*]w^* - k$$

Applying a tie-breaking rule whereby the employer implements the technology when indifferent between adopting ($D = 1$) and non-adopting ($D = 0$), the employer chooses $D = 1$ when $\Pi^*(1, E) - \Pi^*(1, E) \geq 0$, and $D = 0$ otherwise, which implies that digital monitoring incentives are larger in firms facing an employee organizations iff

$$\Pi^*(1, 1) - \Pi^*(0, 1) \geq \Pi^*(1, 0) - \Pi^*(0, 0)$$

and given the facilitating assumption that $\Pi^*(0, 1) = \Pi^*(0, 0)$, this reduces to $\Pi^*(1, 1) = \Pi^*(1, 0) \geq 0$, that can be written more explicitly as in the expression in Lemma 1 ■