I Z A Institute of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 16362

Contested Transparency: Digital Monitoring Technologies and Worker Voice

Filippo Belloc
Gabriel Burdin
Stefano Dughera
Fabio Landini

AUGUST 2023

I Z A Institute
of Labor Economics
Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 16362

Contested Transparency: Digital Monitoring Technologies and Worker Voice

Filippo Belloc
University of Siena

Gabriel Burdin
University of Leeds and IZA

Stefano Dughera
University of Torino

Fabio Landini
University of Parma

AUGUST 2023

ISSN: 2365-9793

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Contested Transparency: Digital Monitoring Technologies and Worker Voice*

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. Finally, in an exploratory analysis, we find a positive association between DM and process innovations, particularly in establishments where ER bodies are present and a large fraction of workers perform jobs that require finding solutions to unfamiliar problems. We interpret these findings through the lens of a labor discipline model in which the presence of ER bodies affect employer's decision to invest in DM technologies.

JEL Classification: M5, J50, O32, O33

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

Corresponding author:
Gabriel Burdin
Leeds University Business School
Maurice Keyworth Building
LS2 9JT, Leeds
United Kingdom

E-mail: g.burdin@leeds.ac.uk

* We thank Trevor Young-Hyman for providing extensive and helpful feedback and EUROFOUND for granting access to ECS microdata.

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 raises concerns of fairness, employee dignity, privacy, 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.

In this paper, we address two questions concerning DM utilization at the work-

[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).

place level. First, does the existence of employee representation (ER), and related collective bargaining procedures over DM utilization, help or hinder the adoption of these technologies? Second, does the presence of ER bodies increase or attenuate the effect of DM technologies on firm performance? To investigate these questions, 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 labor 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, hence, enhances 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] Third, DM exerts a positive *productivity effect* by providing more accurate and timely information on the production process, facilitating on-the-job training, organizational learning and better managerial decisions.

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 raises implementation costs by forcing the employer to bargain over the utilization of DM and reduces the disciplining and productivity effects of DM by restricting the actual utilization of information collected by DM tools. In addition, ER mitigates workers' negative behavioural reactions to monitoring by improving the accountability of DM systems (e.g. enforcement of

[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).

safeguard procedures on how monitoring data is used by the firm).[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 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 the 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

[4]Qualitative evidence from recent case studies 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).

[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 shaping the use of these technologies and their effect on innovation.

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 monitoring technologies. We also document additional exploratory evidence showing that in establishments with ER and a larger fraction of workers performing jobs that require finding solutions to unfamiliar problems, the use of DM technologies is associated with a higher probability of introducing process innovation.

The paper contributes to different strands of literature in economics, industrial relations and organization studies.[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-developed system of collective bargaining and employee representation in corporate decisions exists (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 in relation to the workplace governance of these technologies (Eurofound, 2020), little is known about the actual impact of such reg-

[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.

ulatory 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). According to this view, employers invest in technologies that increase the observability of human work and enhance the credibility of the threat of dismissal as a labor discipline mechanism, facilitating 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). While these approaches predict a positive effect of monitoring on worker performance, empirical evidence is mixed. Some studies have credibly shown that IT-based monitoring technologies reduce extreme forms of employee misconduct (e.g. theft) and improve sales productivity in specific contexts (Pierce et al., 2015).[9] 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, existing studies on data analytics technologies indicate that productivity gains from these technologies largely depend on the coexistence of other complementary organizational practices and capabilities (Aral et al., 2012; Wu et al., 2020, 2019). We contribute to this literature by analyzing how workplace employee representation correlates with the use of DM and moderates its relationship with innovation. Interestingly, our exploratory analysis suggests that DM coupled with employee voice mechanisms is associated with a higher incidence of process innovations in workplaces where a large fraction of the workforce is oriented to solve unfamiliar production problems. This is consistent with experimental evidence documenting negative effects of monitoring on performance precisely in innovation-prone production environments characterized by task complexity and multidimensional performance (Belot and Schröder, 2016; Herz and Zihlmann, 2021). Organization studies

[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.

[9] Other studies have focused on the effect of monitoring on other behavioural dimensions, such as shirking and absenteeism (Hubbard, 2000; Duflo et al., 2012).

on the effect of work transparency also show that preserving zones of privacy around workers' activities is necessary to improve performance, particularly in production settings that require experimentation and innovative problem solving. (Bernstein, 2012). Our findings suggest that ER seems to increase the innovation effectiveness 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 reactions.

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 discuss our main findings, both from our correlational analysis and regression discontinuity approach. Section 5 concludes.

2 The model

We analyze a two-stage, partial-equilibrium, labor-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.[10] 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

[10]This implies 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, workplace body of employee representation 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) find zero wage effects of shop-floor employee representation in Finland, where sectoral collective bargaining coverage remains high. Third, since the level of the minimum wage may affect the workers' perception of what constitutes as 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).

$y'(e) > 0$ 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 case, he receives his outside option $w_0 \geq 0$.

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

[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 recorded as a dummy variable.

(ii) *Disciplining effect*—DM-generated data on worker activity eases labour surveillance and enhance 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 $c(e, 1) - c(e, 0) > 0 \forall e > 0$.

(iv) *Productivity effect*—DM-generated date on worker activity improves 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 $\pi(e, 1) - \pi(e, 0) > 0 \forall e > 0$.

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 , recording 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 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 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

[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 show 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.

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

All four channels listed in the previous section may be reasonably affected by the presence of a firm-level body of employee representation, as detailed in the following list.

(i) *Implementation cost*—By forcing the employer to negotiate over the use of digital monitoring, the employee organization imposes an additional bargaining costs that increases the amount of resources that must be must sunk to implement the technology, so that $k(D) \equiv k(D, E)$ and $k(1, 1) > k(1, 0) \geq k(0, E) = 0$.

(ii) *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 $1 \geq \mu(1, 0) > \mu(1, 1) \geq \mu(0, E) > 0$.

(iii) *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 $c(e, 1, 0) > c(e, 1, 1) \geq c(e, 0, E) > 0 \forall e > 0$.

(iv) *Productivity effect*—By imposing governance constraints on the use of DM-generated data, employee representation limits the informational gains allowed for by the digital tool, so that $\pi \equiv \pi(e, D, E)$ and $\pi(e, 1, 0) > \pi(e, 1, 0) \geq \pi(e, 0, E) \forall e > 0$.

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 – that $\pi(e) = \alpha e$ and $c(e) = \delta e^2/2$, where $\alpha \equiv \alpha(D, E) > 0$ and $\delta \equiv \delta(D, E) > 0$ are two shifters that satisfy assumption iv and iii respectively (productivity and commitment effects), so that $\alpha(1, 0) > \alpha(1, 1) \geq \alpha(0, E)$ and $\delta(1, 0) > \delta(1, 1) \equiv \delta(0, E)$. 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 – $\alpha(1, E) - \alpha(0, E) > 0$ – but the employee's morale deteriorates – $\delta(1, E) - \delta(0, E) > 0$ – and all three effects are smaller when the employee organization is in place – $\mu(1, 0) - \mu(1, 1) > 0$, $\alpha(1, 0) - \alpha(1, 1) > 0$, 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. Moreover, recall that the employee organization increases the implementation cost that must be sunk to adopt the technology (by forcing the employer to negotiate the specific ways in which the digital tool can be used at the workplace), so that $k(1, 1) - k(1, 0) > 0$.

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 organizations increases digital monitoring incentives iff* $\Pi^*(1, 1) - \Pi^*(1, 0) \geq 0$, *or, alternatively, iff*

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

Proof: see the Theoretical Appendix.

As we have just recalled, the term on the r.h.s . of the above inequality is positive since $k(1, 1) - k(1, 0) > 0$ measures the additional bargaining cost that must be sunk to implement the technology when the employee organization is in place. Conversely, and in line with what anticipated in the discussion following Lemma 2, the two terms on the l.h.s. of the of the above inequality are both ambiguously signed. Hence, 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-

[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.

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 to establishments without ER. Moreover, as shown in Figure 2, 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

[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). Finally, 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). Results are available upon request.

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]

4.2 Size-Contingent Regulations: Local Randomization RD analysis

One obvious concern is that 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.[16] We expect these workplace size thresholds provide some exogenous variation in the presence of employee representation, mitigating concerns about 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.[17]

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

[15]One could argue that the presence of ER may induce more adversarial labor-management relations. 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 available upon request indicate that the effect of ER remains positive and significant even when controlling for proxies of labor-management conflict.

[16]In Appendix Table A1, 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).

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

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 size) is discrete and has few mass points (i.e. values of the variable that are shared by many units) in its support[18], 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).[19]

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[20] In Table 5, we report the results of the window selection procedure, including

[18]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.

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

[20]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

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 3 (Panel A) shows evidence of a discontinuity in the presence of ER at the cutoff point. In column (1) of Table 6, 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 6, 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.[21] As shown in Panel B of Table 6, broadly 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 A2 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

predictable demand and very competitive markets.

[21]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).

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 A3).

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 A4 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. Obviously, one immediate consequence of this argument is that, under these conditions, we should observe the firms in which digital monitoring is collectively negotiated to perform better than the others. To check whether this is really the case, in the next section we move to the analysis of firm performance.

4.3 Digital-Based Monitoring, Worker Voice and Innovation

Among the many dimensions that could potentially characterize firm performance, one that has been frequently put in relation to the adoption of advanced digital technologies is innovation. Wu et al. (2020, 2019), for instance, document that the use of data analytics increases the firms' ability to recombine existing technologies and knowledge, leading to higher process innovation. This effect, however, is conditional on a set of firms' organizational features that appear necessary to set the innovative potential of data analytics at work, such as the decentralization of R&D activities. Moreover, the contribution of data analytics to the innovation process seems to be due primarily to the activities carried out by non-inventor employees. Interestingly, an emphasis on process improvements that are achieved through the suggestions received from frontline workers is present also in the transparency literature, and it is actually at the core of the evidence related to potential hiding practices leading to the so-called "transparency paradox" (Bernstein, 2012).

We use in our analysis proxies of performance related to the degree of firms' innovativeness. In particular, we exploit information on whether establishments introduced any new process or product during the last three years. For each item, the survey questionnaire asks the respondent to specify whether the innovation is to be considered new to the market, or new only to the firm. Following Doran and Ryan (2014) we take new-to-market innovation as proxy for radical innovation (although, it should be noted that the very same innovation may have existed on other markets as well) while new-to-firm innovation is conceived as an incremental/imitative innovation, as the product is already available from competitors.

Table 7 shows the results from a series of regressions testing whether the use of digital-based monitoring technologies in conjunction with the presence of ER bodies may favor innovation activities, especially in settings where a significant fraction of the workforce is oriented to perform non-routine tasks (i.e. searching for solutions to unfamiliar problems through trial and error and experimentation). As argued above, these types of skills can be particularly relevant in promoting innovation processes characterized by bottom-up information sharing, as they would rise the innovative content of the information that is exchanged. In columns (1) to (3), we report results from regressions in which the dependent variable indicates whether the establishment adopted any process innovation. We consider all types of process innovations and then distinguish between innovations considered new to the market (i.e. radical) and innovations new to the establishment, but not new to the market (i.e. incremental). In columns (4) to (6), we repeat a similar exercise for product innovations.

Our estimates reveal few interesting patterns. First, the use of digital-based monitoring technologies is positively correlated with innovation activity regardless of the type of innovation. Holding constant other factors, digital monitoring is associated with an increase of 15 (11) percentage points in the likelihood of adopting a process (product) innovation. Second, establishments in which more than 40% of the workforce is oriented to find solutions to unfamiliar problems are more likely to adopt both process and product innovations. Third, the presence of an ER body has no discernible impact on innovation activity. Fourth, the pairwise interaction between ER and digital monitoring is not significant in most specification, although there is some evidence of a negative effect in the case of radical process innovations. This may indicate possible disruptions in the innovation activity at the workplace level due to bargaining impasses over the adoption of monitoring technologies. Fifth, the pairwise interaction between digital monitoring and the fraction of workers oriented to solve non-routine problems has asymmetric effects for radical and incremental innovations. Interestingly, in the case of incremental innovations the interaction is significantly negative. This suggests that increased transparency resulting from the adoption of digital-based monitoring technologies in the presence of a high fraction of workers performing non routine tasks may have detrimental effects on innovation (Bernstein, 2012). Greater perceived surveillance may indeed trigger feelings of mistrust and control-averse reactions in the workforce, inhibiting experimentation, information sharing and other innovation-enhancing behaviours. In contrast, in the case of radical innovations this negative effect does not occur. For this type of innovation, insights and information stemming from frontline workers are less relevant in the innovation generating process, which makes innovation less exposed to the costs of hiding behaviours. Rather, for radical innovation the digital supervision of workers involved in non-routine tasks may improve the ability to collect and analyse dispersed data, which in turn contributes positively to innovation.

Finally, as far as our main theoretical argument is concerned, the three-way interaction among digital monitoring, ER and the fraction of non-routine problem solvers is positive and statistically significant, but only for incremental process innovation. This result suggests that in establishments where most workers have non-routine skills and digital surveillance is embedded within institutions supporting collective employee voice, the chances of introducing incremental improvements in the production process is larger. This is consistent with the idea that in such contexts frontline workers may be more willing to share insights and ideas on potential process improvements, possibly as a result of the negotiation that involved the adoption of monitoring technologies. Instead, this effect is not present in the cases of radical process or product innovations (either radical or incremental), since for these types of innovation bottom-up information sharing by frontline employees play a relatively minor role as a driver of innovation.

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. Interestingly, we also find that digital monitoring coupled with worker voice institutions is positively associated with the likelihood of process innovations in non-routine production settings in which a large fraction of the workforce is engaged in problem-solving tasks.

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, while at the same time supporting firm innovative performance in certain contexts.

References

Acemoglu, D. (2021). Harms of ai. Working Paper 29247, National Bureau of Economic Research.

Acemoglu, D. and Johnson, S. (2023). *Power and Progress: Our Thousand-Year Struggle Over Technology and Prosperity*. Public Affairs.

Adams, Z., Bastani, P., Bishop, L., and Deakin, S. (2017). The cbr-lri dataset: Methods, properties and potential of leximetric coding of labour laws. *International Journal of Comparative Labour Law and Industrial Relations*, 33.

Adhvaryu, A., Nyshadham, A., and Tamayo, J. (2022). An Anatomy of Performance Monitoring. *Harvard Business School Working Paper*, No. 22-066.

Aghion, P., Bergeaud, A., and Van Reenen, J. (2021). The impact of regulation on innovation. Working Paper 28381, National Bureau of Economic Research.

Alchian, A. A. and Demsetz, H. (1972). Production, information costs, and economic organization. *The American Economic Review*, 62(5):777–795.

Aloisi, A. and De Stefano, V. (2022). Essential jobs, remote work and digital surveillance: Addressing the covid-19 pandemic panopticon. *International Labour Review*, 161(2):289–314.

Angrave, D., Charlwood, A., Kirkpatrick, I., Lawrence, M., and Stuart, M. (2016). Hr and analytics: why hr is set to fail the big data challenge. *Human Resource Management Journal*, 26(1):1–11.

Aral, S., Brynjolfsson, E., and Wu, L. (2012). Three-way complementarities: Performance pay, human resource analytics, and information technology. *Management Science*, 58(5):913–931.

Askenazy, P. (2021). Worker surveillance capital, labour share, and productivity. *Oxford Economic Papers*, 74(1):85–93.

Askenazy, P., Breda, T., and Pecheu, V. (2022). Under-Reporting of Firm Size Around Size-Dependent Regulation Thresholds: Evidence from France. AMSE Working Papers 2211, Aix-Marseille School of Economics, France.

Battisti, M., Dustmann, C., and Schönberg, U. (2023). Technological and Organizational Change and the Careers of Workers. *Journal of the European Economic Association*.

Bechter, B., Brandl, B., and Lehr, A. (2022). The role of the capability, opportunity, and motivation of firms for using human resource analytics to monitor employee performance: A multi-level analysis of the organisational, market, and country context. *New Technology, Work and Employment*, 37(3):398–424.

Beckmann, M. and Kräkel, M. (2022). Empowerment, task commitment, and performance pay. *Journal of Labour Economics*, 40(4):889–938.

Belloc, F., Burdin, G., Cattani, L., Ellis, W., and Landini, F. (2022). Coevolution of job automation risk and workplace governance. *Research Policy*, 51(3):104441.

Belloc, F., Burdin, G., and Landini, F. (2023). Advanced technologies and worker voice. *Economica*, 90(357):1–38.

Belot, M. and Schröder, M. (2016). The spillover effects of monitoring: A field experiment. *Management Science*, 62(1):37–45.

Benlian, A., Wiener, M., Cram, W. A., Krasnova, H., Maedche, A., Möhlmanna, M., Recker, J., and Remus, U. (2022). Algorithmic management bright and dark sides, practical implications, and research opportunities. *Business Information Systems Engineering*, 64(6):825–839.

Beraja, M., Kao, A., Yang, D. Y., and Yuchtman, N. (2023). AI-TOCRACY*. *The Quarterly Journal of Economics*. qjad012.

Bernstein, E. S. (2012). The transparency paradox: A role for privacy in organizational learning and operational control. *Administrative Science Quarterly*, 57(2):181–216.

Bernstein, E. S. (2017). Making transparency transparent: The evolution of observation in management theory. *Academy of Management Annals*, 11(1):217–266.

Bloom, N., Davis, S. J., and Zhestkova, Y. (2021). Covid-19 shifted patent applications toward technologies that support working from home. *AEA Papers and Proceedings*, 111:263–66.

Bowles, S. (1985). The production process in a competitive economy: Walrasian, neo-Hobbesian, and Marxian models. *American Economic Review*, 75(1):16–36.

Bowles, S. and Gintis, H. (1988). Contested exchange: political economy and modern economic theory. *The American economic review*, 78(2):145–150.

Bowles, S. and Gintis, H. (1993). A political and economic case for the democratic enterprise. *Economics and Philosophy*, 9:75–100.

Burdin, G., Halliday, S., and Landini, F. (2018). The hidden benefits of abstaining from control. *Journal of Economic Behavior & Organization*, 147:1–12.

Cassar, L. and Meier, S. (2018). Nonmonetary incentives and the implications of work as a source of meaning. *The Journal of Economic Perspectives*, 32(3):215–238.

Cattaneo, M. D., Frandsen, B. R., and Titiunik, R. (2015). Randomization inference in the regression discontinuity design: An application to party advantages in the u.s. senate. *Journal of Causal Inference*, 3(1).

Cattaneo, M. D., Titiunik, R., and Vazquez-Bare, G. (2016). Inference in regression discontinuity designs under local randomization. *The Stata Journal*, 16(2):331–367.

Cattaneo, M. D., Titiunik, R., and Vazquez-Bare, G. (2017). Comparing Inference Approaches for RD Designs: A Reexamination of the Effect of Head Start on Child Mortality. *Journal of Policy Analysis and Management*, 36(3):643–681.

Chang, J. and Lai, L. (1999). Carrots or sticks? a social custom viewpoint on worker effort. *European Journal of Political Economy*, 31:297–310.

Dahl, R. (1985). *Preface to the Theory of Economic Democracy*. Berkeley, CA: University of California Press.

Dauth, W., Findeisen, S., Suedekum, J., and Woessner, N. (2021). The Adjustment of Labor Markets to Robots. *Journal of the European Economic Association*, page jvab012.

Doellgast, V., Wagner, I., and O'Brady, S. (2022). Negotiating limits on algorithmic management in digitalised services: cases from germany and norway. *Transfer: European Review of Labour and Research*, 0(0):10242589221143044.

Doran, J. and Ryan, G. (2014). Firms' skills as drivers of radical and incremental innovation. *Economics Letters*, 125(1):107–109.

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

Duflo, E., Hanna, R., and Ryan, S. P. (2012). Incentives work: Getting teachers to come to school. *American Economic Review*, 102(4):1241–78.

Duggan, J., Sherman, U., Carbery, R., and McDonnell, A. (2020). Algorithmic management and app-work in the gig economy: A research agenda for employment relations and hrm. *Human Resource Management Journal*, 30(1):114–132.

Edwards, M., Charlwood, A., Guenole, N., and Marler, J. (2022). Hr analytics: An emerging field finding its place in the world alongside simmering ethical challenges. *Human Resource Management Journal*, pages n/a–n/a.

Eurofound (2020). Employee monitoring and surveillance: The challenges of digitalisation. *Publications Office of the European Union, , Luxembourg*.

Falk, A., Fehr, A., and Zehnder, C. (2006). Fairness perceptions and reservation wages: The behavioral effects of minimum wage law. *Quarterly Journal of Economics*, 121(4):1347–1381.

Falk, A. and Kosfeld, M. (2006). The hidden costs of control. *American Economic Review*, 96(5):1611–1630.

Frey, B. (1993a). Does monitoring increase work effort? the rivalry with trust and loyalty. *Economic Inquiry*, 31:663–670.

Frey, B. (1993b). Shirking or work morale? the impact of regulating. *European Economic Review*, 37:1523–1532.

Fulton (2020). National industrial relations, an update. *Labour Research Department, ETUI*.

Garicano, L., Lelarge, C., and Van Reenen, J. (2016). Firm size distortions and the productivity distribution: Evidence from france. *American Economic Review*, 106(11):3439–79.

Genz, S., Bellmann, L., and Matthes, B. (2019). Do german works councils counter or foster the implementation of digital technologies? *Jahrbücher für Nationalökonomie und Statistik*, 239(3):523–564.

Gintis, H. (1976). The nature of labor exchange and the theory of capitalist production. *Review of Radical Political Economics*, 8(2):36–54.

Grund, C., Sliwka, D., and Titz, K. (2023). Works Councils as Gatekeepers: Codetermination, Monitoring Practices, and Job Satisfaction. Iza discussion papers, Institute of Labor Economics (IZA).

Harju, J., Jäger, S., and Schoefer, B. (2021). Voice at work. *NBER Working Paper Series*, 28522.

Head, S. (2014). *Mindless: Why smarter machines are making dumber humans*. New York: Basic.

Herz, H. and Zihlmann, C. (2021). Adverse Effects of Contol: Evidence from a Field Experiment. *CESifo Working Paper Series*, 8890.

Hubbard, T. N. (2000). The Demand for Monitoring Technologies: The Case of Trucking*. *The Quarterly Journal of Economics*, 115(2):533–560.

Jarrahi, M. H., Newlands, G., Lee, M. K., Wolf, C. T., Kinder, E., and Sutherland, W. (2021). Algorithmic management in a work context. *Big Data & Society*, 8(2).

Jayadev, A. and Bowles, S. (2006). Guard labor. *Journal of development Economics*, 79(2):328–348.

Jäger, S., Noy, S., and Schoefer, B. (2022). The german model of industrial relations: Balancing flexibility and collective action. *Journal of Economic Perspectives*, 36(4):53–80.

Kasy, M. (2023). The political economy of AI: Towards democratic control of the means of prediction. Technical report.

Kellogg, K. C., Valentine, M. A., and Christin, A. (2020). Algorithms at work: The new contested terrain of control. *Academy of Management Annals*, 14(1):366–410.

Kosfeld, M. (2020). The role of leaders in inducing and maintaining cooperation: The cc strategy. *The Leadership Quarterly*, 31(3):101292.

Lee, D. S. (2008). Randomized experiments from non-random selection in u.s. house elections. *Journal of Econometrics*, 142(2):675 – 697.

Meijerink, J. and Bondarouk, T. (2021). The duality of algorithmic management: Toward a research agenda on hrm algorithms, autonomy and value creation. *Human Resource Management Review*, 33:100876.

Pierce, L., Snow, D. C., and McAfee, A. (2015). Cleaning house: The impact of information technology monitoring on employee theft and productivity. *Management Science*, 61(10):2299–2319.

Prendergast, C. (1999). The provision of incentives in firms. *Journal of Economic Literature*, 37(1):7–63.

Presidente, G. (2023). Institutions, Holdup, and Automation. *Industrial and Corporate Change*, 32(4):831–847.

Reynolds, P. (1973). *Psychological ownership: a study of autonomy and the nature of its association with task commitment*. Durham University Press.

Rogers, B. (2023). *Data and Democracy at Work*. London: Pengiun Rondom House.

Rudorf, Schmelz, Baumgartner, Wiest, Fischbacher, and Knoch (2018). Neural Mechanisms Underlying Individual Differences in Control-Averse Behavior. *The Journal of neuroscience : the official journal of the Society for Neuroscience*, 38(22):5196–5208.

Skillman, G. (1988). Bargaining and replacement in capitalist firms. *Review of Radical Political Economics*, 20(2-3):177–183.

Skott, P. and Guy, F. (2007). A model of power-biased technological change. *Economics Letters*, 95(1):124–131.

Tapscott, D. and Ticoll, D. (2003). *The Naked Corporation: How the Age of Transparency Will Revolutionize Business*. New York: Free Press.

Tursunbayeva, A., Di Lauro, S., and Pagliari, C. (2018). People analytics—a scoping review of conceptual boundaries and value propositions. *International Journal of Information Management*, 43:224–247.

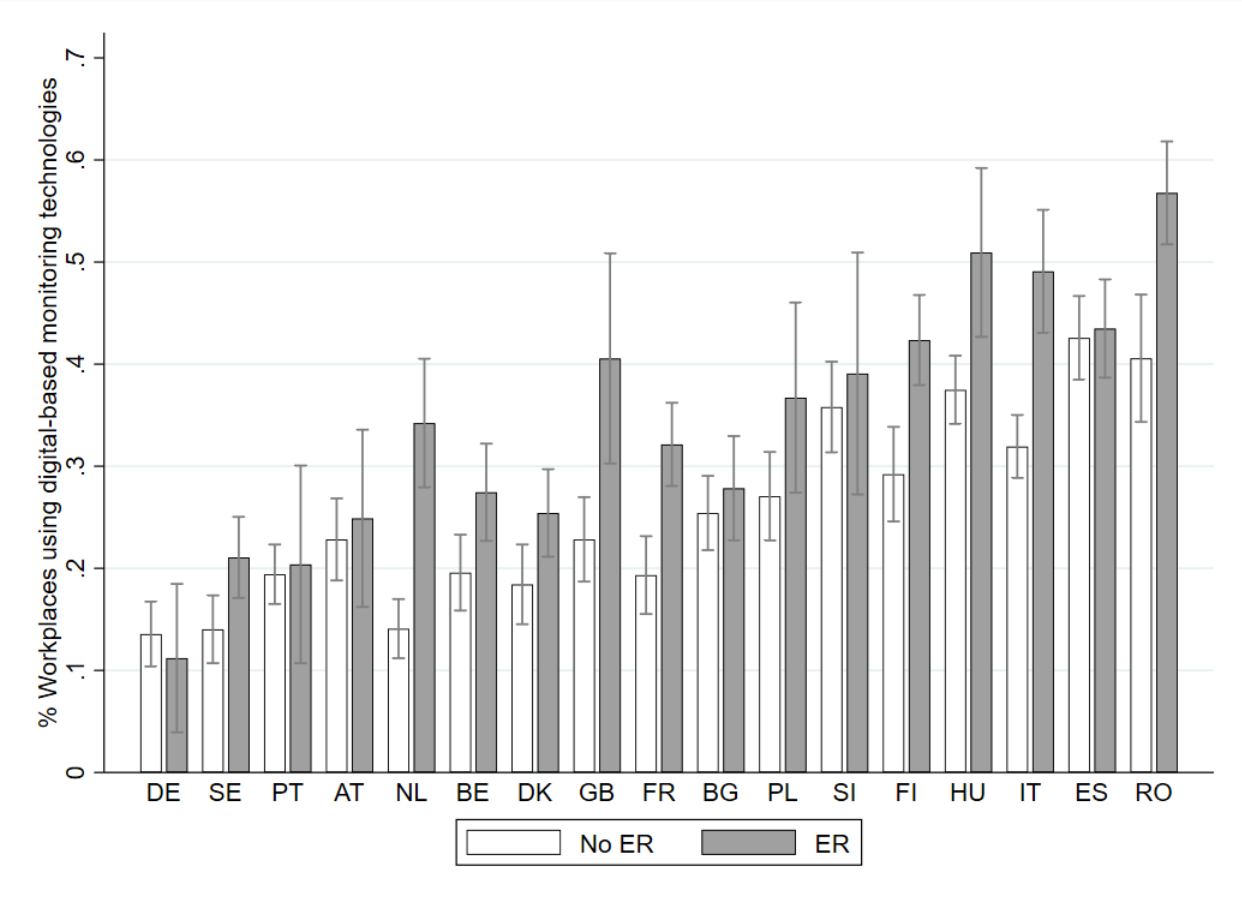
van Houten, G. and Russo, G. (2020). European Company Survey 2019 - Workplace practices unlocking employee potential. Technical report.

Wu, L., Hitt, L., and Lou, B. (2020). Data analytics, innovation, and firm productivity. *Management Science*, 66(5):2017–2039.

Wu, L., Lou, B., and Hitt, L. (2019). Data analytics supports decentralized innovation. *Management Science*, 65(10):4863–4877.

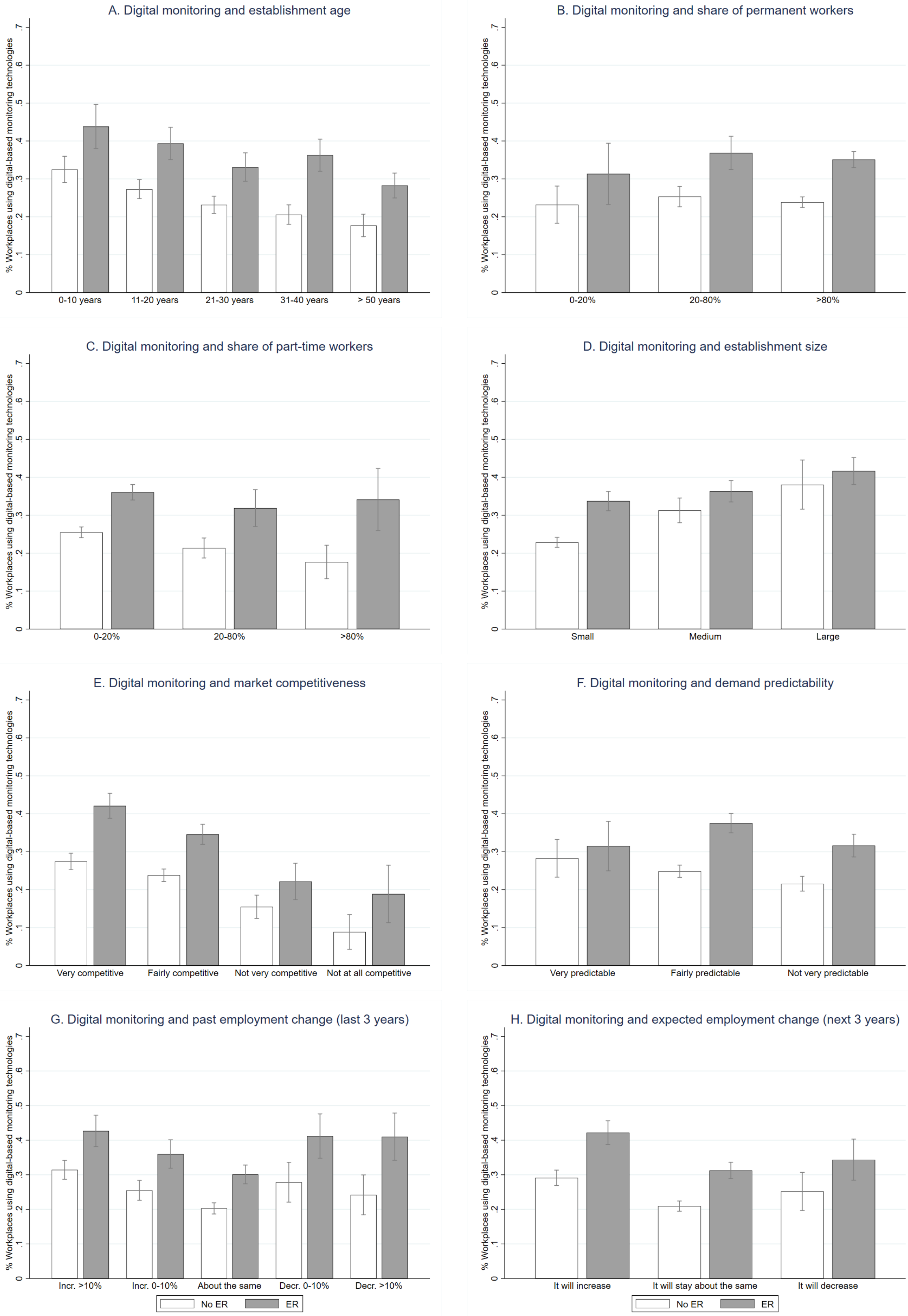
Figures and tables

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



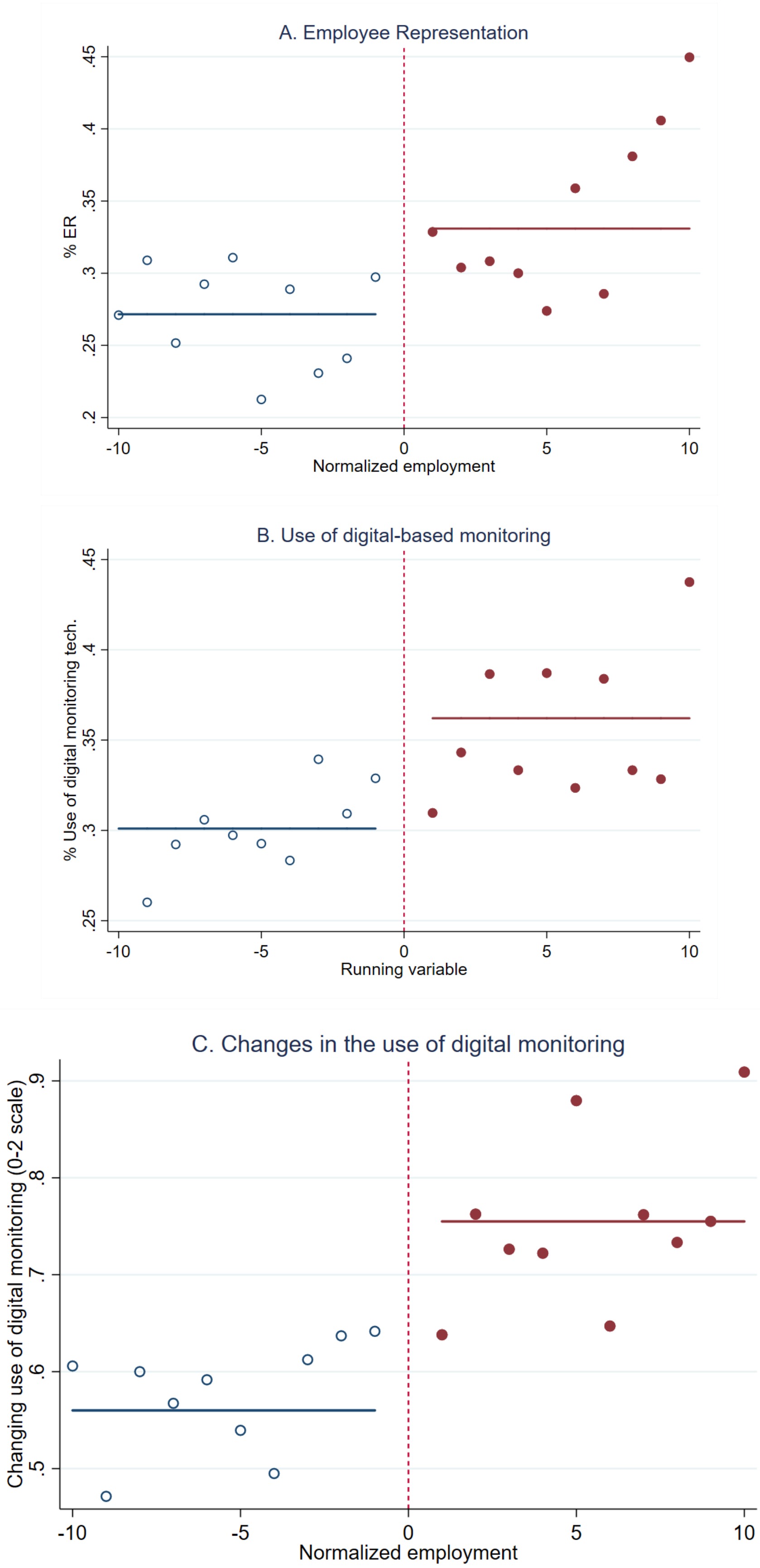
Notes: Pooled data from the European Company Survey 2019 (selected countries). Sample weights are used. The use of digital-based monitoring technologies refers to establishments using "use data analytics to monitor employee performance".

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: 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: 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 6: 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).

Table 7: Digital monitoring, ER, and innovation.

	(1)	(2)	(3)	(4)	(5)	(6)
	Process			Product		
	All	Radical	Incremental	All	Radical	Incremental
Digital monitoring	0.149***	0.036***	0.117***	0.105***	0.040***	0.066***
	(0.011)	(0.007)	(0.011)	(0.011)	(0.009)	(0.010)
ER	-0.003	-0.002	-0.001	-0.007	-0.011	0.003
	(0.010)	(0.006)	(0.010)	(0.011)	(0.008)	(0.009)
% unfamiliar problem solvers > 40%	0.077***	0.030***	0.049***	0.064***	0.048***	0.016*
	(0.010)	(0.006)	(0.009)	(0.010)	(0.008)	(0.008)
Digital monitoring × ER	-0.039**	-0.025**	-0.016	-0.026	-0.020	-0.005
	(0.017)	(0.011)	(0.017)	(0.017)	(0.013)	(0.015)
Digital monitoring × % unfamiliar problem solvers	-0.047**	0.027**	-0.078***	-0.003	0.031**	-0.036**
	(0.019)	(0.013)	(0.018)	(0.019)	(0.016)	(0.017)
ER × % unfamiliar problem solvers	-0.004	0.009	-0.013	0.002	0.001	0.001
	(0.017)	(0.011)	(0.016)	(0.018)	(0.013)	(0.015)
Digital monitoring × ER × % unfamiliar problem solvers	0.082***	0.010	0.076**	0.028	0.003	0.025
	(0.031)	(0.022)	(0.030)	(0.031)	(0.026)	(0.027)
Observations	20,502	20,350	20,350	20,502	20,408	20,408
R-squared	0.114	0.050	0.070	0.109	0.093	0.042

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. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Online Appendix

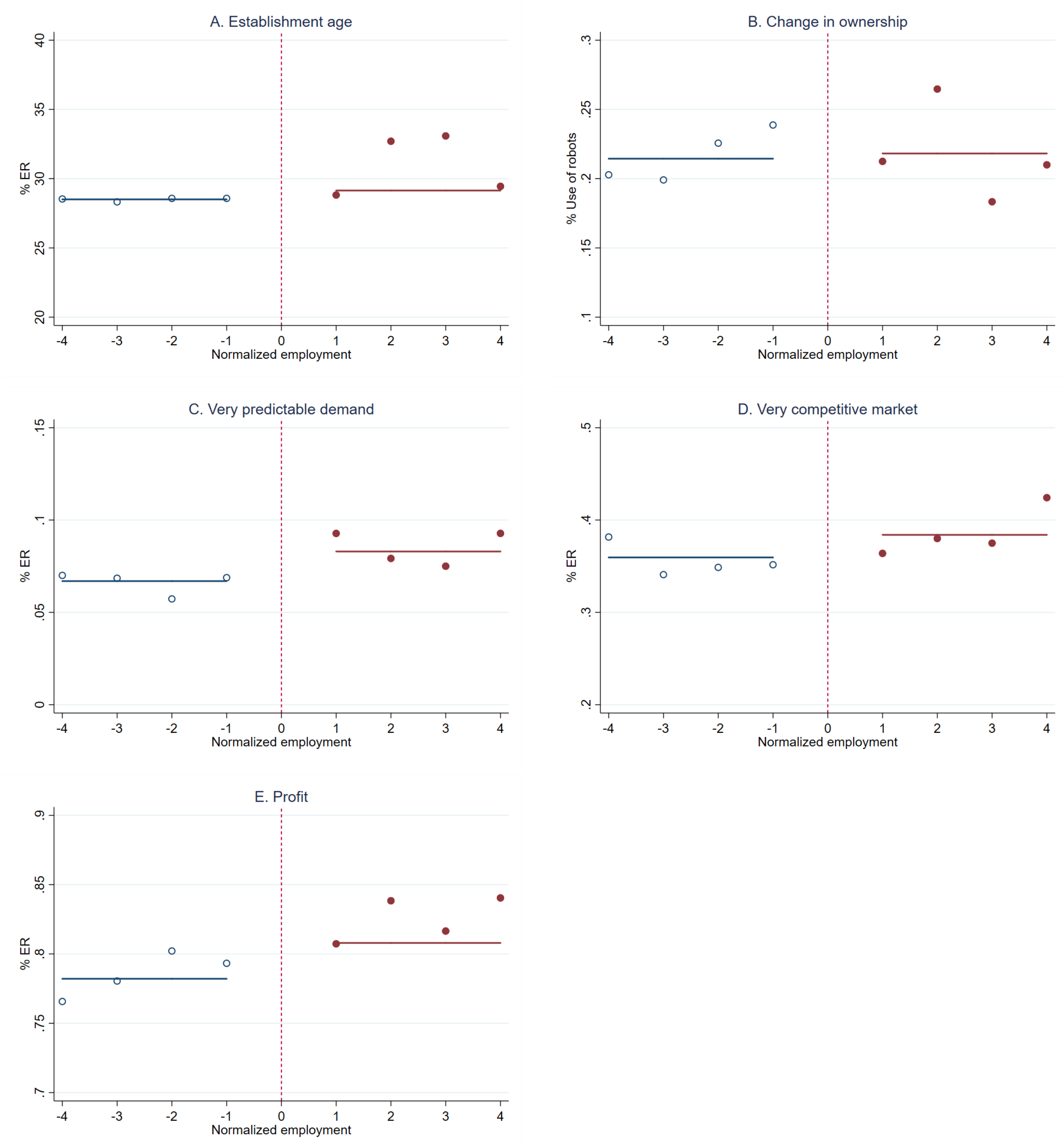
A Supplementary Tables and Figures

Table A1: 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 A2: 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	191
Change in ownership	0.214	0.218	0.004	0.892	193
Predictable demand	0.067	0.083	0.016	0.208	190
Very competitive market	0.360	0.384	0.024	0.273	191
Profit	0.782	0.808	0.026	0.162	183

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 A3: 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 A4: 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

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

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