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ABSTRACT

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This paper analyzes the interplay between the allocation of authority within firms and workers' exposure to automation risk. We propose an evolutionary model to study the complementary fit of job design and workplace governance as resulting from the adoption of worker voice institutions, in particular employee representation (ER). Two organisational conventions are likely to emerge in our framework: in one, workplace governance is based on ER and job designs have low automation risk; in the other, ER is absent and workers are involved in automation-prone production tasks. Using data from a large sample of European workers, we document that automation risk is negatively associated with the presence of ER, consistently with our theoretical framework. Our analysis helps to rationalize the historical experience of Nordic countries, where simultaneous experimentation with codetermination rights and job enrichment programs has taken place. Policy debates about the consequences of automation on labour organization should avoid technological determinism and devote more attention to socio-institutional factors shaping the future of work.

JEL Classification: O33, J51, C73

Keywords: automation risk, job design, employee representation, evolutionary game

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1 Introduction

In the last decade, the discussion about the future of work has been dominated by concerns about the potential labour displacement effects associated with the rapidly evolving applications of artificial intelligence (AI) and robotics. A growing body of research has shown that a substantial fraction of individuals are employed in occupations or perform tasks exposed to a high risk of automation, i.e. occupations or specific tasks that are suitable to be replaced by automation technologies (Frey and Osborne, 2017; Arntz et al., 2017; Nedelkoska and Quintini, 2018; Pouliakas, 2018).[1] While prevailing narratives seem to suggest that high automation risk is an inherent characteristic of certain jobs, we argue that it is also a matter of organisational choice. Indeed, various assessments unveiled that tasks and, hence, automation risk vary substantially within occupations and that such variation may be driven by a wide range of factors, including managerial decisions, workplace organisation, skill availability and industrial relations considerations (Autor and Handel, 2013; Arntz et al., 2017; Spencer and Slater, 2020). Yet, the process through which individual jobs become prone to automation is still poorly understood. In particular, it is often overlooked the fact that the task content associated with a certain job design, an underlying workplace-level driver of automation risk, is the outcome of strategic interactions involving workers and capital owners at the workplace level. As a result, firms' choices over job design can hardly be framed as politics-neutral decisions, purely driven by the search of technical efficiency.

In this paper, we study the organisational drivers of automation risk by focusing on the interplay between job design and workplace governance. We define workplace governance as the set of formal and informal institutions whose function is to allocate control rights within firms. Among such institutions we focus on the role of employee representation (ER), referred to as the institutionalized channel for employee voice through which workers can influence work organisation and employment-related issues at the workplace level (e.g. unions, works councils, consultative committees).

We develop a theoretical framework where we study the relationship between job automation risk and ER using an evolutionary model. We frame our argument with reference to two main research traditions. First the so-called Radical school, which treats technological choices as socially determined (Gintis, 1976; Braverman, 1974; Bowles, 1985; Skillman, 1988; Pagano, 1991). Second the New Institutional view (Coase, 1937; Williamson, 1985; Hart and Moore, 1990), which instead adopts the opposite approach and sees workplace institutions as determined by technology. At the intersection of these two views, we suggest that, under contract incompleteness, job design and workplace governance may

[1] It is worth clarifying that automation risk is a measure of how exposed are jobs to recent technological developments from a purely technological capabilities perspective (Frey and Osborne, 2017). Hence, job automation risk may not necessarily translate into effective subsequent automation or labour-capital substitution.

coevolve as two institutional complements (Aoki, 2001). On the one hand, higher job automatability may reduce the incentives of workers to establish ER bodies, because the increased effort that could be obtained through costly collective action is less than compensated by the benefits that employees gain by working in this kind of job environment. On the other hand, the absence of ER bodies makes automation-prone job designs more convenient for the employers, because it facilitates effort extraction via labour discipline, which is easier to enforce where tasks are simplified. Vice-versa, less automation-prone work environments may favor institutionalized commitment, which in its turn may induce firms to invest in richer job designs. As a result, multiple job design-workplace governance equilibria may coexist. We show analytically that under certain conditions the equilibrium with ER and low automation risk Pareto dominates the one characterised by highly automatable jobs and no ER. The latter can nonetheless emerge as a sub-optimal stable equilibrium that leads to a wedge between private and social benefits and exposes the workers to an inefficiently high automation risk.

We complement our theoretical model with an empirical analysis based on individual-level data from the 2010 and 2015 waves of the European Working Condition Survey (EWCS). The two repeated cross-sections cover in each wave nearly 44000 workers located in 35 European countries and provide harmonized information on a broad range of issues, including detailed information about the task environment of each single worker, such as the degree of task complexity, routineness, involvement of social skills, and task discretion. Moreover, the survey contains information about industry and occupational codes as well as a question concerning the existence of ER bodies at the workplace level.

Our empirical analysis has two main steps. First, we follow the computational strategy of Arntz et al. (2017) and calculate an individual-level measure of automation risk, using the information on task content available in the EWCS data. Doing so, we allow our measure to endogenize the interplay between ER and job design, whilst the use of off-the-shelf measures originally computed on US data would require to assume the exogeneity of job design with respect to the institutional context. Second, we study the empirical relationship between job automation risk and ER through a regression analysis. Given our theoretical argument of a mutually reinforcing relationship between ER and job design, we do not intend to draw causal inference. Nonetheless, in our regressions we control for possible confounding effects due to past automation investments, job insecurity and workplace reorganisations. Our findings indicate that the job design is effectively less automation-prone when ER is present at the workplace. Moreover, the magnitude of the negative correlation between ER and job automation risk appears higher for less educated workers. Our evolutionary framework and documented empirical correlations appear to be compatible with the historical experience and policy developments in Nordic countries, such as Norway and Sweden, where nowadays job automation risk is low and workplace ER is widespread in comparison to other countries.

With these results we contribute to the previous literature in two ways. First, we integrate Arntz et al. (2017)'s original intuition that differences in workplace organisation can explain part of the within-industry and within-occupational heterogeneity of automation risk. In particular, we show that when ER is present, the strategic interaction between workers and capital owners may favor the emergence of job designs characterized by less repetitive and more engaging tasks, which expose employees to lower automation risk. This introduces a socio-institutional source of variation on top of the standard industry-specific and occupation-specific factors. Second, we contribute to research on the relationship between labour institutions and technological change. While previous works focused on the effects of a variety of such institutions (e.g. unemployment insurance, minimum wage laws, ER) on technological investments (Genz et al., 2019; Presidente, 2019; Belloc et al., 2020b) and labour market outcomes (Lordan and Neumark, 2018; Bessen et al., 2019; Parolin, 2020; Dauth et al., 2021), we analyse how job automation risk varies depending on the presence of ER. Despite the relevance of job design and task content for the debates about automation, their dependence on different forms of shop-floor ER has been seldom taken up by the previous literature.[2]

Our analysis highlights how imperfect contracting in employment relationships can shape job design and expose workers to excessively high levels of automation risk, potentially leading to the use of suboptimal technologies. Hence, we provide a potential rationale for the adoption of "so-so technologies', i.e. technologies that displace labour but generate negligible productivity gains (Acemoglu and Restrepo, 2019). Unlike usual culprits identified in the literature, such as distortionary labour institutions and policies, our analysis points to market failures related to the very strategic nature of labour exchanges and the problem of effort extraction at the workplace level. Firms may use job design as a disciplinary tool to improve their bargaining position, biasing workforce skills and subsequent technological choices. In this context, the presence of ER bodies may enable the adoption of rich job designs, retraining policies and complementary technologies that confer large productivity gains.

The remaining of the paper is as follows. Section 2 presents the theoretical framework and develops a simple model of job design and workplace governance coevolution. Section 3 describes the data and discusses the details of our job automation risk measure. Section 4 presents the results of our regression analysis. Section 5 looks at historical examples from the Nordic countries. Section 6 concludes the paper with a discussion of policy implications.

[2]During the 1980s, the microelectronics revolution spurred some interest in the interplay between industrial relations and new technologies (Wilkinson, 1983; Graversen and Lansbury, 1986; Batstone et al., 1987).

2 Theory

2.1 Job design, automation risk and workplace governance

The production of goods and services requires a bundle of tasks to be completed. Each task can be performed either by workers or by capital (machines or software). The set of tasks performed by a worker, which may also include overseeing machines that run other tasks, composes the job of the worker. Firms define the task environment workers are involved in and bundle tasks into jobs, i.e. they shape the "job design". Task characteristics can vary in terms of complexity, variability and routineness. Typically, a rich job design consists of complex, variable and non-routine tasks. By contrast, a poor job design includes simple, standard and routine tasks (Ben-Ner et al., 2012). These task characteristics determine the extent of exposure of certain jobs to automation. Tasks with high complexity and low levels of routineness are often grouped in the literature as 'bottlenecks' to automation (Frey and Osborne, 2017; Arntz et al., 2017; Nedelkoska and Quintini, 2018).[3] By contrast, job automation risk is expected to be higher in the presence of poor job designs. In general, a job design characterised by high automation risk is a necessary, although not sufficient, condition for automation to actually take place.

We argue that the nature of job design cannot be understood in isolation from the features of firm governance. The extent to which employees are informed, consulted and share decision rights with capital owners via institutionalized ER channels shapes the nature of job design, and *vice versa*. Specifically, we propose that these two domains – the job design and its associated automation risk, on the one side, and the workplace governance, as reflected by the presence and the activity of institutionalized channels for collective employee voice, on the other – fit together complementarily and reinforce each other.[4] Although the previous literature offers several insights to understand these mutually reinforcing influence, the joint determination of workplace governance and job design has never been tackled directly in a unified framework. This, instead, is the main aim of this section.

2.1.1 Job design affects workplace governance

Let's start by considering the effect of job design on workplace governance. A central feature of the employment relationship is that work effort cannot be specified in a complete contract. This means that employers face the problem of monitoring and providing the

[3]The richness of job design may be affected by decisions concerning the division of labour among workers: the larger the division of labour, the simpler the tasks assigned to an average worker, and the poorer the job design (Reich and Devine, 1981; Walker, 2020).

[4]This relates to the notion of complementarity, which is at the heart of modern organisational analysis (Brynjolfsson and Milgrom, 2013). In the presence of complementarities, each organisational practice exerts an influence on the profitability of the others, explaining observed patterns of interactions and clustering of practices.

right incentives to motivate workers. Moreover, employers may require workers to invest in firm-specific skills, which expose them to the hazard of opportunistic behaviour on the side of their employer. A central tenet in the new institutional view of the firm is that, whenever these problems arise, property rights would accommodate to provide an efficient solution, minimizing transaction costs and protecting quasi-rents associated with investments in specific assets (Alchian and Demsetz, 1972; Williamson, 1985). In particular, if work effort is hard to monitor and skills are firm-specific, it would be efficient to confer safeguards and control rights to the workers via participation in workplace governance. On the contrary, control rights should remain with capital owners in presence of easy to monitor and general purpose labour.

When applied to job designs, the new institutional view has interesting implications for the structure of workplace governance. In presence of poor job designs and thus high exposition to automation risk, incentive problems related to effort monitoring and skill specificity are mostly irrelevant. Workers are easy to monitor as they perform a set of general purpose, simple and routine tasks. This reduces the need to device workplace governance arrangements in which capital owners share control rights with workers. The opposite holds, however, when job designs are rich and workers are exposed to low automation risk. In such contexts effort monitoring and specific investments are costly activities and a structure of shared workplace governance can improve incentives.

The choice of the workers reinforces such configurations. If a poor job design is selected, workers have no gain other than their monetary compensation (i.e. wage). Numerous empirical studies indeed show that intrinsic motives for work are relatively weak in jobs with narrow scope (see, e.g., Cassar and Meier, 2018; Nikolova and Cnossen, 2020). By restraining from participation in firm governance workers can at least save on the collective action costs needed to establish ER bodies, with the consequence that the latter are unlikely to be introduced.[5] On the contrary, if a rich job design is present, workers may enjoy intrinsic pleasure in carrying out their duties. This implies that they may be more willing to pay the collective action associated with ER and to commit to firm governance.[6] Hence, the risk of substitution of labour with capital affects the structure of the human relations within the firm, alters the outside options of the workers and

[5]Alternatively, one could argue that in presence of poor job designs, the large division of labour among workers rises the cost organizing ER. Task specialization may indeed reduce the opportunities for interpersonal interaction and communication, undermining the formation of solidaristic work groups (Reich and Devine, 1981). This mechanism, which we do not explicitly model, strengthens even further the link between poor job design and absence of ER.

[6]In a dynamic setting the positive association between ER and rich job designs could follow from a negotiation process between workers and owners. Workers may organize in response to a poor job design and negotiate improvements in their working conditions (including richer job content) in exchange for effort commitment. The final outcome would still be the coincidence of rich job designs and ER bodies, but the overall process would start with the introduction of ER within a poor work environment. Since the formalization of such negotiation process would significantly complicate the model, without particular gains in terms of results, we prefer to stick to the simpler argument described in the main text.

ultimately modifies the bargaining powers and the distribution of ownership rights.[7]

2.1.2 Workplace governance shapes job design and automation risk

Symmetrically, it is hard to exclude that the pre-existing structure of the workplace governance is neutral to firm's decisions regarding job design and its associated automation risk. In an incomplete contract environment, firm owners manipulate the job design on strategic grounds and depending on the nature of firm governance they can adopt different solutions.[8] When ER is absent, for instance, owners can benefit from selecting a job design that gradually transforms labour into an easy to monitor and general purpose input, as this may improve their bargaining position vis-à-vis workers and hence increase effort extraction. On the contrary, whenever a structure of ER is present, owners may find it convenient to rely on job designs characterized by a richer task environment, because this can provide intrinsic motivations to the workers and engage them in institutionalized effort commitment.

The idea that causality may be reversed, with property relations and workplace politics exerting an influence on job design, dates back to the early contributions of the Radical economists (Gintis, 1976; Braverman, 1974; Marglin, 1974; Bowles, 1985; Duda and Fehr, 1987; Bartling et al., 2013). According to this view, the conflict of interests over effort provision may induce owners to exercise authority in inefficient ways. In particular, owners may have an incentive to inflate the division of labour among workers and to adapt the job design to general-purpose and easily replaceable competencies (deskilling), increasing the credibility of the threat of dismissal. In our setting, this process implies that the adoption of an automation-prone job design can be driven by labour discipline considerations and not only technical opportunities, leading to an automation risk that is higher than its socially desirable level.

In this context, the presence of ER bodies may be an efficiency-enhancing arrangement. Employee voice in firm governance can create incentives for the design of richer task environments, which can partially mitigate distortions toward excessive automation risk. This can happen through different mechanisms. First, employee representatives may be able to commit to a certain level of group effort in response to a richer task environment, providing an alternative channel to improve work effort compared to labour discipline

[7] Acemoglu et al. (2001) suggest an alternative channel through which technology may contribute to disorganise workers. Skill-biased technical change increases the productivity gap between skilled and unskilled labour, making more costly to sustain wage compression policies in the unionised sector. Thus, technical change undermines the coalition between skilled and unskilled workers and eventually causes de-unionization. On the impact of skill/routine-biased technological change on job polarization see also Goos et al. (2014).

[8] An extensive literature in organisational economics analyses the problem of job design in the context of principal-agent interactions characterized by conflicting interests (Holmstrom and Milgrom, 1991; Itoh, 1994; Baker and Hubbard, 2003). One basic implication from this literature is that, due to incentive considerations, it may be optimal for employers to reduce task variety and group tasks according to their easiness of monitoring (Milgrom and Roberts, 1992).

(Sampson, 1993). Second, employee voice may increase effort commitment by directly reducing its disutility, i.e. strengthening intrinsic motivations (Freeman and Medoff, 1984). Third, at a more general level, worker participation may help to improve information flows and overcome coordination issues (Freeman and Lazear, 1994) and facilitate the enforcement of implicit agreements via relational contracting (Malcomson, 1983; Hogan, 2001).[9] Fourth, unions may help to implement more transparent just-for-cause layoff policies and reduce cyclical layoffs, further improving incentive schemes for long-term investments in skill upgrading.[10] Overall, shared workplace governance structures channelling employee voice and restricting the ability of owners to act unilaterally may reduce the costs of managing difficult-to-monitor labour for the firm, removing perverse incentives for implementing job designs entailing suboptimally high levels of automation risk.[11]

2.1.3 The two-way causation between job design and workplace governance

The two views supporting opposite causality directions (i.e. the job design shaping certain workplace relations in the former, and workplace relations favouring certain job design configurations in the latter) may actually coexist and can be reconciled under the notion of institutional complementarities. Such complementarities refer to situations where the presence of one institutional arrangement in a given domain raises the returns from the adoption of another (thus complementary) institution in a different domain. As a result, complementary institutions tend to arise together and to reinforce each other. While the notion of complementarity is generally used with reference to purely technical activities, its application to institutional settings is now common (Amable, 2000; Aoki, 2001; Hall and Gingerich, 2009; Belloc and Pagano, 2009, 2013; Landini and Pagano, 2020).

Here we advance the argument of a two-way causation in the relationship between workplace governance (and its corresponding distribution of control rights between capital owners and workers) and job design (and its associated automation risk). The arrangements taken in the two domains may influence each other and bring about a multiplicity of "organisational equilibria". In one of them participatory workplace governance arrangements are associated with richer and less automation-prone job designs. In the other, the absence of ER combines with high automation risk. While the emergence of multiple organisational equilibria has been already modelled in the literature,[12] to the best of our

[9] Schöttner (2008) shows that the possibility of engaging in relational contracts may facilitate the use of richer job designs characterized by multitasking and broad task assignments.

[10] Carmichael and MacLeod (1993) shows that multiskilling, i.e. training workers in more than one job (e.g. job rotation) is linked to job security, conferring firms an advantage in process innovations. Che and Yoo (2001) demonstrate that team production and job security are complementary to group-based incentives and peer sanctions.

[11] Barth et al. (2020) exploit exogenous changes in tax subsidies to union members in Norway and show that increasing firm-level union density has a positive effect on both productivity and wages.

[12] Pagano and Rowthorn (1994) develops one of the first formalization of organisational equilibria comparing capitalists and worker-managed firms. Landini (2012, 2013) uses a similar approach to model organisational diversity in knowledge-intensive industries, such as software. Barca et al. (1999) and Earle

knowledge the application of this analytical framework to understand the interplay between workplace governance structures and job designs embedding different automation risks has never been examined. In the following section we present a simple model that helps elucidating the underlying mechanisms of this relationship.

2.2 A simple model

2.2.1 Stage game

Consider an industry populated by two groups of agents: owners (o) and workers (w). Agents o and w contribute to production by interacting within firms, whose organisation depends on two domains: job design (D) and workplace governance (G). D reflects the average proportion of different tasks that are assigned to each worker (i.e. division of labour): the smaller (larger) such proportion, the less (more) varied and more (less) repetitive the tasks assigned to each worker and the poorer (richer) the job design. Poor (rich) job designs exhibit relatively high (low) automation risk. G is associated with the existence of institutionalized forms of ER, e.g. unions, work councils, consultative committees. Agents o choose in domain D and have two alternatives: high (D_H) and low (D_L) automation risk. Agents w choose in domain G and have two alternatives too: with (G_H) and without (G_L) ER.

Agents o and w choose in their respective domain of choice to maximize individual utility. In particular, o selects the job design that maximizes utility u_o for a given type of workplace governance, while w selects the type of workplace governance that maximizes utility u_w for a given job design. Notice that, in this framework, the actions of o and w involve two distinct causalities: the actions of o captures Radical's causality running from workplace governance to job design, whereas the actions of w imply the reversed New Institutional causality running from job design to workplace governance.

Every period, workers employed in a given firm decide on their optimal level of effort e_w ($\in [0, 1]$) by looking at the type of job design and workplace governance in place. In particular, we assume that effort decisions are driven by two factors: institutionalized commitment, i.e. workers commit via ER to exert higher effort in exchange for richer job design[13]; and labour discipline, i.e. workers can be induced via job design to exert higher effort under the threat of their contract being terminated. Labour discipline is higher in job designs characterized by repetitive and routine tasks, which make shirking easier to be detected.[14] Moreover, we assume that workers earn a fixed wage and sustain a collective

et al. (2006) provide empirical evidence supporting the view of organisational equilibria as a suitable concept to study the heterogeneity of corporate governance models.

[13]In Table A.2.1 in Appendix, using data from a large sample of European workers, we show that the presence of ER correlates positively with different measures of good workplace climate and commitment (worker motivation, manager-employee trust and mutual cooperation).

[14]In Figure A.2.2 in Appendix, we show that that subjective job insecurity is increasing in job automation risk.

action cost to organize ER at the plant level. Formally, we write w's utility as follows:

$$u_w(D,G) = s + \lambda m(D,G)e_w - e_w^2/2 - a(D)(1-e_w)\theta/r - c(G) \tag{1}$$

where $s(>0)$ is the baseline wage, λ (>0) is the marginal benefit of committed effort, $m(D,G)$ is a functional parameter such that $m(D_L,G_H) = 1$ and $m(D_H,G_L) = m(D_H,G_H) = m(D_L,G_L) = 0$ (i.e. committed effort only occurs in presence of a rich job design), $e_w^2/2$ is the convex cost of effort,[15] $a(D)$ is the easiness of effort monitoring, with $a(D_H) = 1$ and $a(D_L) = 0$, $c(G)$ is the cost of collective action, with $c(G_H) = c > 0$ and $c(G_L) = 0$, θ (>0) is difference between the net benefit in present job and net benefit in the next best alternative, and r is the probability of labour reinstatement. Following Acemoglu and Restrepo (2019) we interpret the latter as a factor affecting the length of unemployment spells, which depends both on technology (e.g. number of alternative tasks available in the economy) and institutions (as they affect the reallocation of displaced workers to new jobs). Overall, the ratio θ/r captures the so-called cost of job termination (Bowles, 1988).

From the maximization of equation (1) with respect to e_w it follows that:

Remark 1: *The optimal level of e_w is given by the effort extraction function $e_w^*(D,G) = \lambda m(D,G) + a(D)\theta/r$, where $\lambda m(D,G)$ captures effort exertion via institutionalized commitment and $a(D)\theta/r$ effort exertion via labour discipline.*

Agents o's utility depends on two components: baseline sale returns, which depends positively on worker effort, and wages. Hence, we write o's utility as follows:

$$u_o(D,G) = qe_w - s \tag{2}$$

where $q(>0)$ is the value of output per unit of work done.

The firm-level interaction between o and w can be represented in game theoretic form by the triplet $\Gamma = \{I, \Sigma, u\}$, where $I = \{o, w\}$ is the set of players, $\Sigma = D \times G$ is the set of strategy profiles, and $u = \{u_o(\sigma), u_w(\sigma)\}$ for $\sigma \in \Sigma$ is the vector function of the players' payoff, where $u_o(\sigma)$ and $u_w(\sigma)$ are given by equations (2) and (1). Table 1 reports the normal-form representation of game Γ (for the derivation of payoffs see Appendix A.1). Let us introduce the following definitions:

Definition 1: *A design-governance arrangement in game Γ corresponds to a pure strategy profile $\sigma = \{\sigma_o, \sigma_w\} \in \Sigma$ where $\sigma_o \in D$ and $\sigma_w \in G$ is the pure strategy adopted by players o and w, respectively.*

[15] For the sake of simplicity we assume an explicit and easy to manage function for the cost of effort. Main results hold using alternative functional forms.

A specific way of organizing production at the plant level corresponds to each design-governance arrangement. In particular, game Γ offers a representation of four distinct arrangements, namely $\{D_H, G_H\}$, $\{D_H, G_L\}$, $\{D_L, G_H\}$ and $\{D_L, G_L\}$. In this set, we are interested in the combinations that qualify as self-sustaining equilibria:

Definition 2: *An arrangement $\sigma^* = \{\sigma_o^*, \sigma_w^*\}$ is a design-governance equilibrium if the corresponding strategy profile is a Nash equilibrium (NE) of game Γ.*

The following proposition holds (all proofs are in Appendix A.1):

Proposition 1: *In game Γ there exist two values $\bar{r} = \theta/\lambda$ and $\bar{c} = \lambda^2/2$ such that: i) if $r < \bar{r}$ or $c > \bar{c}$, then $\{D_H, G_L\}$ is the only design-governance equilibrium; ii) if $r > \bar{r}$ and $c < \bar{c}$, then two design-governance equilibria exist, namely $\{D_H, G_L\}$ and $\{D_L, G_H\}$.*

At the population level a design-governance equilibrium represents an organisational convention, meaning that conforming to it is a mutual best response as long as virtually all members of each population (owners and workers) expect virtually all members of the other to conform to it. According to Proposition 1 the number and types of conventions existing in the industry depends on the probability of labour reinstatement r and the cost of collective action c. When the former is relatively low or the latter is large, D_H and G_L is the unique organisational convention. Indeed, a low r rises the cost of job termination, which makes effort extraction via labour discipline particularly effective. This in turn makes D_H a dominant strategy in Γ. Similarly, a large c implies that the organisation of ER tends to be expensive and G_L is a dominant strategy as well. On the contrary, when both these conditions are violated, best responses depend on the choices made by the counterparts. In particular, if r is sufficiently large, labour discipline is not effective as effort extraction mechanism and owners find it convenient to rely on institutionalized commitment when an ER body is established. At the same time, if c is low, workers find it convenient to support the cost of collective action and commit to higher effort in presence of richer job design. It follows, that job design and workplace governance exhibit complementarities and two organisational conventions exist, namely $\{D_H, G_L\}$ and $\{D_L, G_H\}$.

In presence of multiple organisational conventions, it is interesting to characterize their relative efficiency. In particular, we derive the following result:

Proposition 2: *Suppose $r > \bar{r}$ and $c < \bar{c}$. If θ/r is sufficiently low, then the organisational convention $\{D_L, G_H\}$ Pareto dominates convention $\{D_H, G_L\}$.*

The intuition behind Proposition 2 is straightforward and relates to the combined

effect of the probability of labour reinstatement and the cost of collective action. If r is large enough, o is better-off under $\{D_L, G_H\}$ than under $\{D_H, G_L\}$, because institutional commitment represents a more profitable strategy of effort extraction compared to labour discipline. With respect to w, if the cost of job termination θ/r is sufficiently small, the worker will not attach great value to the job relationship under $\{D_H, G_L\}$. In particular, we obtain that for the range of c's values such that G_H is a best response to D_L, a low θ/r implies that w is also better-off under $\{D_L, G_H\}$. It follows that under these conditions, two conventions exist and $\{D_L, G_H\}$ Pareto dominates $\{D_H, G_L\}$.[16]

2.2.2 Dynamics

To provide a framework for studying asymptotic stability[17] we restrict the analysis to the space of parameter in which two organisational conventions exist and introduce an explicit model of the dynamics of change. In every time period, $n_o(>0)$ owners and $n_w(>0)$ workers are randomly paired to play the stage game described in Table 1. Let $\delta(\in [0,1])$ be the fraction of o adopting the strategy D_H and $\gamma(\in [0,1])$ be the fraction of w adopting the strategy G_H. The status of the industry can thus be described by the pair $\{\delta, \gamma\}$. Assuming that the size of the industry is sufficiently large, $\{\delta, \gamma\}$ will also denote the probability with which agents meet across types. On this basis, for any given value of γ we can write o's expected payoffs as follows:

$$V_H^o = \gamma(q\theta/r - s) + (1-\gamma)(q\theta/r - s) \tag{3}$$

$$V_L^o = \gamma(q\lambda - s) + (1-\gamma)(-s) \tag{4}$$

for strategies D_H and D_L respectively. Similarly, for any given of δ, the expected payoffs to workers are, respectively:

$$V_H^w = \delta(s - \theta/r + \theta^2/2r^2 - c) + (1-\delta)(s + \lambda^2/2 - c) \tag{5}$$

$$V_L^w = \delta(s - \theta/r + \theta^2/2r^2) + (1-\delta)s \tag{6}$$

These expected payoff functions are illustrated in Figure 1.

To model the co-evolution of job design and workplace governance, suppose that

[16] It is important to stress that this result holds before actual automation takes place. In other words, we are not considering the potential productivity gains that can be associated with the effective adoption of automation technologies. On this respect, however, some recent contributions (e.g. Acemoglu and Restrepo, 2019) highlight that in many instances such gains tend to be limited, thus broadening the validity of our results.

[17] A glossary of technical terms used in this section is provided in Appendix A.1. For further reference see Bowles (2004).

both o and w update their strategy by best responding to the distribution of types in the previous period. In particular, suppose that the updating process works as follows. In any time period both o and w are exposed to a cultural model randomly selected from their own group. For instance, an owner, named A, has the opportunity to observe the job design selected by another owner, named B, and to know her expected payoff with a probability α. If B has selected the same job design as A, A does not update. But if B has selected a different job design, A compares the two payoffs and, if B has a greater payoff, switches to B's job design with a probability equal to $\beta(>0)$ times the payoff difference, retaining her own job design otherwise (where β is a constant reflecting the greater effect on switching of relatively large differences in payoffs, appropriately scaled so that the probability of switching varies over the unit interval). The same procedure takes place among workers hired in different firms. It is easily shown that this process of payoff monotonic updating gives the following replicator equations:

$$\Delta\delta = \delta(1-\delta)\alpha\beta(V_H^o - V_L^o) \tag{7}$$

$$\Delta\gamma = \gamma(1-\gamma)\alpha\beta(V_H^w - V_L^w) \tag{8}$$

where $\Delta\delta$ and $\Delta\gamma$ are the changes in job design and workplace governance between any two period. Equations (7) and (8) represent a system of differential equations which describes how the distribution of types $\{\delta, \gamma\}$ changes over time. Given this dynamics, we are mainly interested in the stationary states of the economy, namely the states for which $\Delta\delta = 0$ and $\Delta\gamma = 0$. Such states represent fixed-points of the dynamical system, and organisational equilibria of the industry.

Proposition 3: *Suppose $r > \bar{r}$ and $c < \bar{c}$. Then, the dynamical system composed of equations (7) and (8) is characterized by five organisational equilibria: $\{0,0\}$, $\{0,1\}$, $\{1,0\}$, $\{1,1\}$ and $\{\delta^*, \gamma^*\}$, with*

$$\delta^* = \frac{\lambda^2 - 2c}{\lambda^2} \qquad \gamma^* = \frac{\theta}{r\lambda} \tag{9}$$

Out of these five equilibria, only two are asymptotically stable, namely $\{0,1\}$ and $\{1,0\}$; equilibrium $\{\delta^*, \gamma^*\}$ is a saddle, whereas equilibria $\{0,0\}$ and $\{1,1\}$ are unstable.

The vector field in Figure 2 offers a graphical representation of the content of Proposition 3. The arrows represent the out-of-equilibrium adjustment. For states $\delta > \delta^*$ and $\gamma < \gamma^*$, $\Delta\delta$ is positive and $\Delta\gamma$ is negative and the industry will move to $\{1,0\}$. This state corresponds to the organisational convention characterized by high automation risk and no ER. Analogous reasoning holds for states $\delta < \delta^*$ and $\gamma > \gamma^*$, where the industry con-

verges to $\{0, 1\}$. In this case, the stable state corresponds to an organisational convention characterized by low automation risk and the creation of ER bodies. In the remaining regions of the state space, namely south-west and north-east, we may identify a locus of states (dashed upward-sloping line) for which the system will transit to the interior equilibrium $\{\delta^*, \gamma^*\}$, with states above the locus transiting to $\{1, 0\}$ and below the locus to $\{0, 1\}$. State $\{\delta^*, \gamma^*\}$ is stationary, but is a saddle: small movements away from it are not self-correcting. Two additional unstable stationary states are $\{0, 0\}$ and $\{1, 1\}$, but are of no interest. All the area above the dashed upward-sloping line represents the basin of attraction of $\{1, 0\}$ and all the are below it the one of $\{0, 1\}$. These two corner solutions are thus the absorbing states of the dynamic process. If the industry is ever at either of these states, it will never leave.

The dynamics represented in Figure 2 suggests that, over time, the industry is likely to converge to one of two very different conventions. In one of them, namely $\{0, 1\}$, a homogeneous population of owners selecting a job design characterized by low automation risk interacts overtime with workers establishing ER bodies. In the other, namely $\{1, 0\}$ a population dominated by owners selecting a job design with high automation risk interact with workers that do not establish ER bodies. According to Proposition 2, the convergence to one convention as opposed to the other does indeed have implications in terms of overall efficiency, in that $\{0, 1\}$ Pareto dominates $\{1, 0\}$.

The extent to which one of these two equilibria will actually be the organisational convention of the industry depends on two interrelated factors. First of all, for any size of the basin of attraction, the emergence of $\{1, 0\}$ as opposed to $\{0, 1\}$ (and *vice versa*), is more likely, the more probable the initial distribution of types in the economy to fall in $\{1, 0\}$'s (or $\{0, 1\}$ in the opposite case) basin of attraction. This implies that history matters and there exists path dependency in the way the industry evolves. Second, for any given initial distribution of types, the emergence of one of the two absorbing states as the final resting point of the dynamics depends on the size of its basin of attraction. In particular, the greater the basin of attraction of one state relative to the other, the more likely such state is to become the organisational convention of the industry. On this respect, it is important to notice that $\partial\delta^*/\partial c < 0$, $\partial\gamma^*/\partial\theta > 0$ and $\partial\gamma^*/\partial r < 0$. This implies that, increases in the cost of collective action c and in the difference between net benefits in the present job and in the next best alternative θ as well as reductions in the probability of labour reinstatement r make the Pareto inefficient convention $\{1, 0\}$ more likely to emerge (see Figure 3). These parameters are affected by a wide range of factors, including institutional settings and technological conditions. For instance, unconditional unemployment benefits such as universal basic income, lower the value of θ and they thus reduce $\{1, 0\}$'s basin of attraction. The same effect would obtain in presence of labour market institutions that either make the process for establishing ER bodies easier (i.e. they reduce c) or improve the allocation of displaced workers to new tasks (i.e. they rise

r). Conversely, the high economy-wide incidence of technologies that displace workers without creating new job opportunities, e.g. so-so technologies, tends to reduce r and thus makes the socially inefficient outcome more likely to emerge.[18]

3 Empirical approach

3.1 Aim of the empirical analysis

The theoretical model sketched out in the previous section emphasizes the interplay between workplace governance structures conferring partial control rights to employees and job design. In particular, the main argument that is put forward is that the existence of ER bodies favours the adoption of job designs characterized by rich task content, leading to a negative association between ER and individuals' exposure to job automation risk. With the following econometric analysis, we aim at looking whether the empirical evidence is consistent with this theoretical argument.

We proceed in two main steps. First, we need to measure job automation risk in a way that accounts for the variation in individual task content within occupations. Hence, we compute an individual-level measure of automation risk by using a rich array of information on the actual content of the tasks performed by workers, so as to allow our measure to endogenize the interplay between ER and job design. Second, we explore the empirical relationship between our measure of job automation risk and ER through a regression analysis, where the effects of possible confounding factors, including past automation investments, job insecurity and workplace reorganisations are accounted for. Although we do not aim at drawing causal inference, our empirical strategy allows us to verify the overall empirical consistency of the model.

3.2 The European Working Condition Survey: overview

We base our empirical analysis, including the computation of a measure of automation risk at the job-level, on individual-level data from the last two waves of the European Working Condition Survey (EWCS) conducted in 2010 and 2015 (Eurofound, 2012; 2017). This is a

[18]The comparison between the two organizational conventions can also help to rationalize some recent findings concerning the differential displacement effect of automation technologies across institutional settings. For instance, such effect tends to be stronger in US (Acemoglu and Restrepo, 2020) than in Germany (Dauth et al., 2021). In our framework this result can be explained by the fact in Germany ER bodies are more common than in US, which implies that job designs are richer and tasks are more difficult to automatize. This does not necessarily imply that in Germany automation proceeds less fast; rather, that it tends to be guided more by technical considerations than by disciplinary motives. Interestingly, Battisti et al. (2020) show that unions contribute to smooth the transition of workers from routine to abstract tasks within German firms in response to technological changes, by facilitating re-training and skill upgrading. This is consistent with the idea that ER bodies may favor job designs that enhance the complementary between labor and new technologies.

well-known data source to study working conditions in Europe (see, for example, Aleksynska, 2018; Cottini and Lucifora, 2013; Nikolova and Cnossen, 2020). EWCS data cover a representative sample of European workers, comprising roughly 44.000 observations per wave (more than 1000 observations per country in each wave). A crucial advantage of this survey is that it provides harmonized cross-country information on individual attributes, task environment, occupational codes, working conditions and presence of ER bodies. This allows us to take into account the possible influence of ER on the task content for each single job, whilst crosswalking off-the-shelf measures originally computed on US data (e.g., Frey and Osborne, 2017; Autor and Dorn, 2013) would require to assume the exogeneity of job designs with respect to the institutional context. While the survey is conducted every five years since 1990, our analysis is restricted to 2010-2015 due to the availability of key information, such as variables identifying the presence of ER at the workplace level and detailed 4-digit occupational codes.[19] The last waves also provide richer information on the task environment faced by each individual.

We focus on institutionalized forms of ER. In particular, we exploit the question asking individuals to report the presence of a "trade union, works council or a similar committee representing employees" at the company level. This definition does not include ad-hoc forms of representation and individual schemes of employee involvement. Alongside ER, a wide range of individual and firm-level characteristics are reported as part of the survey. In our analysis, we include all those variables that have been found relevant in this research context by previous literature. In particular, we include age, gender and education of the worker (education is measured as a categorical variable for primary, lower/upper/post-secondary and tertiary level education), the size of the firm (as coded in three classes: 1-9/10-249/250+ employees), occupation and industry dummies. Importantly, in all our regressions we also add a job-level variable for the worker's use of computers at work.[20] This helps us to account for the pre-existing adoption of automated technologies (on the link between the use of computer-assisted technologies and automation see Zolas et al., 2020).

Our final sample consists of repeated cross-section individual-level data from the common set of countries included in the two EWCS waves: the 27 Member States, Turkey, Norway and the UK. In addition, we restrict the analysis to salaried workers, excluding self-employed, unemployed and inactive individuals. Descriptive statistics for the final sample are reported in Table 2.[21]

In the following section we illustrate the procedure to compute our preferred measure

[19]We are grateful to Eurofound for granting access to a secure version of the survey including 4-digit ISCO codes.

[20]Computer use is captured by a dummy variable equals one if the individual's main job involves working with computers or laptops at least one quarter of the time.

[21]We exclude observations from Kosovo, Serbia and Switzerland throughout the analysis as these countries were not part of both waves. We also exclude German respondents in 2010 due to lack of information on education.

of individual-level automation risk. Other measures are introduced as part of robustness checks in section 4.2.

3.3 Measuring job automation risk

In order to calculate individuals' automation risk scores based upon the task content of each job, we closely follow the task-based risk approach proposed by Arntz et al. (2017). First, we crosswalk the occupation-specific automation risks as obtained by Frey and Osborne (2017) for 702 O*NET occupations in US to our 4-digit ISCO codes. While crosswalking occupational codes always introduces potential measurement errors, the fact that we use highly disaggregated occupation categories (4 digits) reduces assignment problems faced by previous studies.[22] Second, we regress Frey and Osborne's occupation-level automation risk scores on a set of self-reported charteristics reflecting the task content of inidviduals' job. These task variables are aimed at representing the engineering bottlenecks emerging from the experts' discussion (perception and manipulation, creative intelligence and social intelligence), i.e. tasks that are difficult to automatize (Frey and Osborne, 2017). Descriptive statistics for the 9 task-related variables representing the engineering bottlenecks identified by Frey and Osborne (2017) are reported in Table 2.[23] In Appendix, Table A.2.2, we also report the marginal effects of task attributes on automation risk. Overall, we find the expected signs. Automation risk is negatively correlated with the utilization of social skills ("dealing directly with people", "visiting customers") and creative skills ("solving unforeseen problems", "complex tasks", "learning new things", "applying own ideas", "influencing important decisions"). In contrast, there is a positive association between automation risk and jobs involving "monotonous tasks". Taken together, these correlations point to describing automation risk as a synthetic measure of the suitability of the job design to facilitate the codification of human tasks into programmable machines.

In order to follow Arntz et al. (2017) as close as possible, the regression also accounts for differences related to gender, age, income, education, sector and supervision responsibilities.[24] Estimated coefficients capture the effect of job-related attributes on the automation risk of individuals' occupation. Similar to Arntz et al. (2017), we follow a multiple imputation approach in the case of individuals assigned with multiple automation scores and use an Expectation-Maximization (EM) algorithm to cope with measurement errors. Finally, we use the estimated coefficients to obtain a prediction of automation risk at the level of individuals' jobs. Instead of assuming an average task structure at the

[22]For example, Arntz et al. (2017) assign Frey and Osborne's automation scores to 2-digit occupations in PIAAC.

[23]We follow the categorization of these additional variables as closely as possible to Arntz et al. (2017), although the variables in the EWCS do not always match accurately.

[24]Whilst these additional variables are unlikely to have a direct effect on job automation risk, their inclusion is aimed at picking up differences in self-reported task environment across individuals.

occupational level (Frey and Osborne, 2017), our approach captures the variation in non-automatable tasks within occupations (Arntz et al., 2017). This is our baseline measure of automation risk for each individual (Model 1). In Table 2, we report the descriptive statistics of both the baseline task-based automation risk variable computed as in Arntz et al. (2017) and the occupation-based automation probability measure computed as in Frey and Osborne (2017). In line with previous studies, the use of occupation-based approach result in a larger share of workers exposed to high risk of automation than the task-based approach.[25]

Our theoretical framework suggests a negative correlation between the incidence of workplace governance structures granting control rights to workers and the prevalence of automation-prone job designs. In Figure 4, we preliminary analyse the plausibility of the argument by plotting the country-average automation risk calculated as explained above against the fraction of individuals reporting the presence of ER at the workplace level. The figure reveals substantial differences in workplace governance institutions (i.e incidence of ER) across countries. There is a negative association between the incidence of ER structures and job automation risk. Higher incidence of ER is associated with lower automation risk. In Figure 4, we also report the relationship between the incidence of ER and the residuals from a regression on automation risk on a constant and GDP per-capita. The negative association between job automation risk and ER persists, even after purging our measure from the effect of cross-country differences in living standards.[26]

4 Results

4.1 Baseline analysis

In order to study the association between automation risk and ER, we proceed with a systematic regression analysis. We exploit the individual-level dimension of the EWCS data and consider the following baseline regression model:

$$\mathrm{AR}_i = \beta_0 + \beta_1 \, \mathrm{ER}_i + \mathbf{b}\mathbf{X}_i + \varepsilon_i \tag{10}$$

where AR_i is an individual-level measure of automation risk computed as explained in the previous section; ER_i is a dummy variable which equals 1 when an employee representation

[25]Figure A.2.1 in Appendix compares the average automatability score obtained in our sample with estimates reported by Arntz et al. (2016) using PIAAC. Despite some differences in the level of job automation risk, our measures positively correlate with the one reported by Arntz et al. (2016). While for most countries the average of automation risk remains substantially similar between 2010 and 2015, small variations over time can be observed in some cases. These changes may be due to recomposition effects associated with country or industry-level shocks. To account for these factors, we estimate regressions including both country and industry specific time trends.

[26]Figure A.2.3 in Appendix reports differences in task-related attributes by ER presence, suggesting ER is indeed associated with less automation-prone task environments.

body is established at the workplace where the worker i is employed and 0 otherwise, and β_1 is the associated parameter; $\mathbf{X}_i$ is a large vector of controls (including: individual-level and firm-level controls, country dummies, industry dummies, time dummies, country-specific and industry-specific time trends, and occupational ISCO dummies); ε_i are the residuals.

The estimation is carried out on the pooled sample over the two EWCS waves referring to 2010 and 2015. The results are reported in Table 3. In column 1, we regress automation risk on a dummy variable that takes value one for workers reporting the presence of ER structure at their workplaces. The association between ER and automation risk is negative and significant. In columns 2-6, we sequentially add more controls to see the robustness of this correlation. In column 2, estimates control for differences in individual characteristics (gender, age and education). We find that female workers are more exposed to jobs at a higher risk of automation as well as younger individuals, though the effect of age is non-linear. Similar to previous studies (e.g., Arntz et al., 2016; Nedelkoska and Quintini, 2018), we document that higher educational levels reduce the risk of automation at the individual's job level. In column 3, we control for the effect of firm size and for the use of computers at the workplace, which is a proxy for the utilization of digital technologies. In column 4, we add country, industry and year effects. Estimates reported in column 5 control for industry and country-specific time trends, which help us to account for sectoral and country-level patterns of past automation.[27] Finally, in column 6, we report the results from a demanding specification in which we soak up all the variability across broadly defined occupations.[28] The estimated parameter of ER remains negative and statistically significant across all the model specifications, consistently with our theoretical argument. In the most complete specification, ER is associated with a 2.2% reduction in automation risk.

To better disentangle the interactions between ER and individual characteristics of the workers with respect to the risk of automation, we estimate a logit model using a high risk of automation dummy as the dependent variable. We consider a dummy which equals 1 when the automation risk variable used in the first regression round is equal to or greater than 0.7, and which equals 0 otherwise (Frey and Osborne, 2017; Arntz et al., 2016; Nedelkoska and Quintini, 2018). Marginal effects from the logit estimation are reported in Table 4.

[27]Clearly, automation trends vary also at the job-level; however, the component of such trends that is driven by exogenous technological or institutional shocks is likely to have a significant aggregate dimension.

[28]Occupation-level fixed effects also help to account for cross-sectional variability in the physical burden for the workers due to different working conditions across jobs (this may be a relevant source of heterogeneity, if more physically demanding jobs are associated with different incentives to establish ER). Moreover, to account for within-occupation heterogeneity of working conditions we run additional tests where we control for job characteristics involving tiring/painful positions and carry/moving heavy loads (available upon request). The main results hold.

Estimates are qualitatively similar to those obtained by the pooled OLS regressions, with the sign of the association between ER and automation risk being again negative and strongly significant. After controlling for individual and firm-level characteristics, the presence of ER is associated with a reduction of 3.5 percentage points in the probability of being exposed to high risk of automation (column 6 of Table 4). For example, this is equivalent to roughly half of the reduction in automation risk associated with the use of a computer at work. As for the conditional effects shown in Figure 5, we find that the magnitude of the (negative) correlation between ER and high automation risk dummy is consistently higher for less educated employees. ER structures may help to insulate less-educated workers from the risk of automation by reshaping their task environment.[29]

4.2 Robustness checks and additional analysis

Job automation risk: measurement issues. The procedure to compute our baseline task-based measure of automation risk (Model 1) closely follows Arntz et al. (2017). To assure robustness, we compute alternative task-based measures of automation risk. First, the inclusion of individuals' income among the regressors in our baseline model leads to a substantial drop in the number of observations due to missing values. Hence, we also estimate the model excluding the income variable (Model 2). Second, we estimate an additional model excluding individual and firm-level characteristics. This model only accounts for within-occupation variation in the 9 task-related variables described in section 3.2 (Model 3).[30] In Table 5, we show that the negative correlation between automation risk and ER is robust to these modifications, both when automation risk is measured as a continuous variable (columns 1-3) and when it is measured as a dummy equal to 1 if automation risk is equal to or greater than 0.7 (columns 4-6). Interestingly, we observe that the magnitude of the coefficient associated with ER when automation risk is computed without controlling for individual characteristics (Model 3) represents a lower bound of ER (negative) effect, whilst the estimated correlation between ER and automatability appears to be stronger when automation risk is computed by absorbing worker characteristics. A possible explanation for this difference is that a number of individual characteristics correlate both with automation risk and ER presence, and hence controlling for these characteristics in the computation of the risk variable helps reducing a bias in the estimation of ER effects.

Bivariate probit estimates. Our framework highlights the mutually reinforcing relationship between ER and workers' exposure to automation risk via job design. Hence, we do not intend to perform a causal analysis. Nevertheless, potential unobserved con-

[29]For example, ER may compensate lower formal education credentials by fostering intensive investments in job training and firm-specific skills (Belloc et al., 2020a).

[30]In Appendix Figure A.2.4, we compare the distribution of automation risk according to all these models.

founders correlated with both ER and automation risk may affect the conclusions even in a descriptive analysis. For instance, bad managers may be prone to implement poor job designs, exposing workers to high automation risk. Moreover, the presence of a bad manager may also induce workers to demand organisational safeguards via the implementation of ER bodies. If that is the case, our baseline correlation between ER and automation risk should be upward biased, i.e. the previous estimates would be higher (less negative) than the true parameter.

We address the problem for unobserved confounders by using a simultaneous bivariate model which imply the estimation of the joint probability distribution of ER and high automation risk. More precisely, we use a recursive bivariate probit model (Greene and Hensher, 2010), in which the error terms of the two equations are assumed to be correlated. The parameters in the system of two equations are identified by imposing an exclusion restriction, i.e. the equation determining ER presence includes at least one variable that is believed to be correlated with ER, but does not have a direct effect on automation risk. As exclusion restriction, we use the share of individuals employed at workplaces with ER bodies computed for detailed industry-country cells. We use the share of individuals employed at ER-workplaces per industry-country cell in 2010 as an instrument for individuals' ER status in 2015. The assumption is that the share of individuals employed at ER-workplaces defined for narrow industry-country groups shifts individual's probability of being employed in a ER-workplace, but has no direct effect on individuals' automation risk. After controlling for other individual and firm-level factors, the instrument affects automation risk only through the shift in the individual's probability of being employed at ER-workplace. An aggregated instrument is less likely to be related to unobserved individual characteristics.[31]

Table 6 reports the estimates of the recursive bivariate probit model. The determinants of job automation risk are simultaneously estimated with the determinants of the probability of being employed at ER-workplace. The aggregate share of individuals employed at ER-workplaces computed for each industry-country group is significantly correlated with the individual's probability of being employed in an establishment with ER. A Wald test rejects the hypothesis that the errors in both equations are independent, at conventional levels ($\chi^2(1)= 9.171$, with p-value of 0.003). The marginal effect suggests that ER is associated with a 13 percentage points reduction in the probability of being exposed to high automation risk. The positive value of ρ suggests that the univariate probit estimate is upward biased.

Past automation. The documented negative correlation between the presence of ER bodies and job automation risk may simply reflect the fact that highly automatable jobs have already been replaced by automation technologies. As Arntz et al. (2016) point

[31]The use of aggregate instrument is common in the literature on employee representation and works councils (Devicienti et al., 2018; Jirjahn, 2010).

out, low automatibility may result from the fact that unused potential for automation has been exhausted. Indeed, there is some indication that the presence of ER fosters the actual utilization of robots and other AI-related technologies (Belloc et al., 2020b). For this reason, all our previous estimates account for common technological shocks via the inclusion of country and industry-specific time trends and control for individuals' use of computers at work.

To further understand whether our results are driven by past investments in automation technologies, we perform a series of additional estimates in which we directly control for robot density at the industry-country level. To do this, we merge information on the operational stock of robots (per 1000 workers) with the individual-level EWCS data. Our measure of robot density is computed using data from the International Federation of Robotics (IFR) and employment figures from Eurostat. We restrict the analysis to the sub-sample of individuals employed in industry-country cells for which the matching between IFR and EWCS data is feasible. The industry-level classification has been converted as to obtain fifteen industries, roughly corresponding to the classification used by IFR: 1) Agriculture, 2) Mining, 3) Food, beverages and tobacco, 4) Textiles, 5) Paper, 6) Wood and furniture, 7) Plastic and chemicals, 8) Non-metallic mineral products, 9) Metal, 10) Electronics, 11) Automotive, 12) Other transport equipment, 13) Electricity, gas and water supply, 14) Construction, and 15) Education and R&D. This excludes a large part of the sample made of individuals employed in retail and service sectors. Our measure of robot density is computed for 2009 and 2014 and, hence, is lagged one year in relation to job automation risk, ER status and the other individual-level variables. Results are reported in Table 7. In columns 1-2, we look at the correlation between ER and job automation risk, as in Table 3. In columns 3-4, we re-estimate the logit models reported in Table 4. We add controls for robot density in columns (2) and (4). Reassuringly, the negative correlation between ER and automation risk holds even after controlling for the actual utilization of automation technologies.[32]

Competing mechanisms. Our theoretical framework emphasizes the complementarity between ER and rich job designs entailing low automation risk. The key underlying mechanism in our model is that ER serves as an effort commitment device. There are of course alternative mechanisms that could drive the relationship between ER and automation risk, which are not explicitly considered in our framework. For example, the fear of machine-labour substitution resulting from high job automatability might induce workers to engage in ER and bargain for richer, and thus less automation prone, job designs. Moreover, one may argue that ER makes it harder for firms to fire workers thereby raising the costs of organisational restructuring leading to the introduction of new automated technologies, including the required job re-design toward automation. To

[32]Robot density and job automation risk are positively correlated. One possible explanation is that environments characterized by high automation potential are conducive to more robot usage.

account for these competing channels, we estimate our main models adding controls for individual's self-reported level of job insecurity and exposure to workplace reorganisation. We measure perceived job insecurity by considering whether respondents tend to agree or strongly agree with the statement *"I might lose my job in the next 6 months"*. Individuals' exposure to workplace reorganisation is captured by a dummy that takes value 1 if respondents answer positively to the following question *"During the last three years has there been a restructuring or reorganisation at your current workplace which affected your immediate working environment?"*. As reported in Table 8, the negative correlation between ER and job automation risk holds even after the inclusion of these additional controls. As expected, there is a positive and significant association between perceived job insecurity and our measure of individual's exposure to automation risk. Instead, the correlation between automation risk and workplace reorganisations is negative.

5 Historical examples

Both our theory and econometric analysis support the argument of a complementary fit between job design and workplace governance. In particular, the dynamics of our model points to the possibility of two opposed evolutionary patterns, where ER and richer job designs either reinforce or weaken each other over time. In line with this, our empirical analysis has showed that job automation risk and the presence of ER are negatively correlated in a large international sample of workers. However one may wonder whether this result is also consistent with the historical experience of the countries covered by our study. In this section, we focus on the group of countries most likely positioned at the one hand of the spectrum, namely Sweden and Norway, which exhibit relatively low job automation risk, high union coverage and widespread workplace ER in comparison to other countries.[33] By looking at the policy developments of these countries, particularly during the 1960s and 1970s, we can obtain additional insights on the mechanisms underlying the mutual reinforcing dynamics between job design and workplace organisation highlighted in our theoretical framework.

Bolweg (1976) provides a general overview of the intense debates and developments on industrial democracy and job redesign initiatives that took place in Norway during the 1960s. First, the so-called Cooperation Project, started in 1962, was a research initiative funded by trade unions, employers federation and the state. The first phase of the project analysed experiences of formal arrangements granting ER at the board level. The second phase investigated the condition for fostering personal participation at the shop-floor

[33]Moreover, Figure A.2.5 in Appendix shows that while Nordic countries have by far the largest share of workers in establishments with ER (panel A), their estimated distribution of automation risk lies more to the left than the distribution for other groups, indicating lower average automation risk for these countries (panel B).

level through changes in job content and autonomous work groups aimed at eliminating Tayloristic work practices. According to the emerging job design principles, jobs had to be challenging, provide enough variety and novelty, facilitate active and continuous learning, multi-skilling and allow for greater worker's discretion in deciding the nature of tasks and pace of work. A crucial aspect of this new approach was the notion that firms can select and adapt technology to enrich job content. For this reason, several experiments took place at the level of individual companies to facilitate the diffusion of rich and engaging job designs alongside participatory governance structures. In the language of our model these experiments can be interpreted as exogenous shifts in the distribution of owner and worker types, which favoured the tipping towards the basin of attraction of the convention with widespread ER and low automation risk.

In addition, important legislative changes took place during this period. In 1966, the Basic Agreement between Norwegian unions and employers federations was revised and provided the general framework for the operation of works councils in undertakings employing more than 100 employees. Works councils were entitled with full information and consultation rights over financial and organisational issues. In 1973, the Norwegian Company Act was amended to include provisions granting employees the right to appoint representatives in company boards and the obligation to establish a corporate assembly (with 1/3 worker representatives) in companies employing more than 200 employees. The aim of these new workplace governance structures was to extend the involvement of employee representatives far beyond bargaining over wages and working hours, including matters such as major investments, organisational changes and labour reallocations. In 1977, the new job design principles introduced by some companies in the context of the Cooperation Project were incorporated into the Norwegian Work Environment Act (Deutsch, 1986). Overall, these different legal initiatives reduced the institutional costs associated with the creation of ER bodies, thus making the ER-equilibrium even more absorbing (see Figure 3 above). As a result, production conventions characterized by rich job designs and shared governance arrangements started to emerge in many Norwegian industries. Such conventions, which persisted over time, helped containing the excessive recourse to job routinization as tool for labour discipline, resulting in a lower exposition of Norwegian workers to automation risk compared to other countries.

During the 1960s and 1970s, similar developments took place in Sweden, where concerns about the negative effects of Tayloristic job designs characterized by high degree of specialization, monotony and routinization (e.g. assembly-line production) for worker productivity and well-being also became widespread among union leaders and employers. Pilot experiments involving the redesign of jobs and new factories started to proliferate. These initiatives were aimed at permitting workers to vary their tasks, to gain a better understanding of the production process as a whole, exercise more control over the pace for work and provide a less alienating work experience. Several case studies discussed

these developments. For example, Rosner and Putterman (1991) describe the case of the Volvo's Kalmar factory, which began operations in the early 1980s. In this plant, the assembly line was replaced by a series of parallel workstations managed by small autonomous teams of workers trained to perform and rotate between tasks. Aguren and Edgren (1980) document the initiatives of Swedish Employers Confederation (SAF) in the 1970s. Employers developed major job redesign projects in hundreds of plants, the so-called "new factories", responding to problem of high absenteeism, turnover and low product quality. These bottom-up initiatives were supplemented by nationwide legislation that gave unions the right to negotiate over non-wage workplace issues and supported worker participation at different organisational levels (Martin, 1987). It became evident that organisational changes required complementary modifications in workplace governance, i.e. the authority structure of firms. First, the 1976 Co-determination Act stipulated that employers must negotiate with the unions before deciding on any major changes in the business operations, such as long-term decisions involving work organisation, tasks, methods, training, etc. (Sandberg et al., 1992). Second, the 1977 Work Environment Act aimed at improving occupational health and working conditions. The new legal framework stated that technologies, the organisation of work and the content of work must be designed in such a way that the employee is not subjected to physical strain or mental stress that may lead to illness or accidents. Importantly, the law required workplaces employing at least 50 employees to set up a safety committee consisting of representatives of the employer and of the workers.

Similarly to the Norwegian case, the combination of experimentation in work arrangements and ad-hoc legislative interventions led Sweden towards a trajectory that favored the diffusion of rich job designs and participatory governance structures. Traditional collective bargaining institutions aimed at negotiating wages and immediate working conditions between unions and employers evolved to include shop-floor communication channels, board-level employee representation and codetermination rights through which workers can exert an influence on work organisation, job design and technology implementation. This allowed workers' ideas to be considered and gave employees formal decision-making powers in areas that were previously considered exclusive prerogatives of firm owners and managers. Through this new institutions, workers had a voice in relation to the introduction of new technologies, which were directed to facilitate the transition to richer job designs, eliminate heavy and repetitive tasks and generate large productivity gains (Aguren and Edgren, 1980; Rosner and Putterman, 1991).[34] Altogether, the reinforcing dynamics between job design and workplace governance favoured the emergence

[34]Our account of the Nordic experience does not neglect the importance of other context-specific factors that may have contributed to increase the pressure for redesigning jobs and introducing productivity-enhancing technologies, such as labour market tightness, limited availability of foreign workers and strong competitive pressures on low productivity firms resulting from solidaristic wage policies (Barth et al., 2014).

of a production context in which shared control rights and rich job designs co-exist. This production context contributed to reduce the exposition of Swedish workers to excessive automation risk.

In sum, the historical experience of Nordic countries is revealing of the two-way relationship suggested by our framework. When faced with the problem of abandoning the Tayloristic equilibrium to achieve a more balanced and socially preferred configuration, these countries engaged in a wide range of policy experiments and legal initiatives that had two aims: fostering greater participation in firm governance on one side, and favoring the introduction of richer job designs on the other. Interestingly, ER institutions did not operate as a force against technological advancements. Some of these countries register a comparatively high number of per-worker industrial robots (IFR, 2019). Even more interesting is the fact that early robotization was introduced exactly during the period of intensive policy experiments aimed at improving work arrangements (Aguren and Edgren, 1980; Deutsch, 1986). The co-existence of widespread ER institutions and rich job designs appeared to favor the selection of efficiency-enhancing technologies, which at the same time has supported the improvement of working conditions.

6 Discussion and conclusions

Previous research has documented substantial within-occupation variation in task content and, hence, individuals' exposure to automation risk (Arntz et al., 2016). In this paper, we focused on the role played by workplace organisation and, in particular, industrial relations, in explaining such pattern. We developed an evolutionary theoretical framework linking the presence of ER bodies and job designs entailing varying degrees of automation risk in a two-way relationship: on the one hand, automation-prone job designs make ER less likely to be established, because workers do not expect to gain much by organizing labour in very standardized work environments; on the other, ER facilitates the implementation of rich job designs characterized by low automation risk, as it favours group effort commitments thereby and reduces the need for employers to convert complex tasks into routine and easier to monitor assignments. Using individual-level data from EWCS and computing worker-level measure of automation risk based on a set of task content characteristics, we documented a negative correlation between ER and individuals' automation risk. The observed empirical pattern holds even after controlling for a wide range of factors and is consistent with our proposed organizing framework.

It is worth acknowledging some limitations of our study. First, while we document an inverse relationship between the presence of ER and automation risk, we provide only indirect evidence on the competing mechanisms suggested by our model, i.e. the use of job design as a discipline device versus high-performance norm and skill upgrading sustained by the presence of ER. However, the historical experience of Nordic countries, in

particular Norway and Sweden, suggests that the channels highlighted in our organizing evolutionary framework are plausible. Moreover, we document a positive correlation between the presence of ER bodies and self-reported measures of worker motivation and trusting worker-managers relationships. Second, the cross-sectional structure of the data makes it difficult to rule out that unobservable factors drive the simultaneous selection of individuals into workplace governance structures and task environments. Further research based on longitudinal data could analyse the dynamic of task content for individuals exposed to different workplace governance institutions (Battisti et al., 2020). Third, in our framework the possibility of effort extraction via institutionalized commitment may require the existence of an industrial relation system characterized by a strong cooperative culture and trust. In particular, one may wonder whether this is actually a precondition for the role assigned to ER in our model. However, historical evidence reveals that the extent to which workplace cooperation is a prerequisite or a byproduct of granting workers control rights is unclear.[35]

Our paper contributes to contemporary policy discussions in relation to the governance of the automation process (Goldfarb et al., 2019; Savona, 2019; Goos, 2018). It does so in three distinct ways. First, it expands the *menu of policy options* available to policy-makers dealing with the impact and prospects of new technologies. In particular, the paper highlights the role of industrial relations as an additional institutional lever shaping job design and, hence, the pace and direction of the automation process at the workplace level. As suggested by our basic model, when confronted with disorganized labour, capital owners have the incentives to rely on job designs in which the share of automation-prone tasks is excessively high. The reason is that in a world of incomplete contracts, the exposition of workers to high automation risk can serve as a labour discipline device that enables greater effort extraction. In these cases, the introduction of ER bodies represents a decentralized labour institution that helps re-balancing authority relations within firms, allowing workers and capital owners to coordinate on a socially superior organisational equilibrium. Whilst industrial and social insurance policies aimed at favouring the selection of technologies involving large productivity gains and protecting displaced workers are undoubtedly important, our study adds that a relevant role is to be played by the institutions that help labour organisation at the job-level.

Second, the paper suggests that the *design of interventions* governing the automation process needs to be forcefully multi-dimensional. This directly follows from our theoretical framework, in which workplace governance and job design fit together complementarily and lead to the existence of multiple organisational equilibria. A core implication is that, in order to shift from one equilibrium to the other, simultaneous changes

[35]For instance, Norway and Sweden experienced the high levels of industrial conflict in the world in the 1920s and early 1930s, way before developing their social democratic policies and labour institutions (Moene and Wallerstein, 2006)

along multiple organisational domains are needed. Targeting only reforms in workplace governance institutions is not sufficient. Efforts need to be made to engage capital owners in gradual re-design of their productive endeavours, favouring the adoption of skillful and rewarding jobs.

Finally, the paper identifies key socio-economic contextual factors affecting the efficacy of ER and job design-related interventions. In particular, the comparative analysis carried out on the basins of attraction of the two organisational equilibria reveals that three factors are of particular relevance: the cost of collective action, the distribution of net benefits across different job and unemployment positions and the probability of labour reinstatement. While the latter depends on a combination of technological and business-cycle factors (e.g. unemployment rate and consequent availability of job opportunities), the former two are driven primarily by socio-economic forces. For instance, regulations making the process for requesting the implementation of codetermination and shop-floor ER structures more complex for workers increase the collective action cost associated with ER and thus make the ER-equilibrium less likely to emerge.[36] Similarly, the absence of unconditional unemployment benefits tends to increase the difference between net benefits in the present job and in the next best alternative. As a consequence labour discipline becomes relatively effective as a effort extraction mechanism (due to the high costs associated with loosing one's job), thus making the equilibrium with no ER and poor job design more absorbing. Hence, the study suggests foundations and basic building blocks of a *unified policy governance framework* aimed at managing the adoption pace, direction, risks and societal impacts of technological change in the age of automation.

[36]The role attributed to collective action costs in our framework is particularly relevant given the progressive erosion of collective bargaining institutions in Europe (e.g. Addison et al., 2017), and the rise of alternative work arrangements (Katz and Krueger, 2019), in which setting up traditional forms of employee representation may be more difficult. In the context of a more flexible and fluid work environment, alternative forms of worker voice would be necessary.

References

Acemoglu, D., Aghion, P., Violante, G.L., 2001. Deunionization, technical change and inequality. Carnegie-Rochester Conference Series on Public Policy 55, 229–264.

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

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

Addison, J., Teixeira, P., Pahnke, A., Bellmann, L., 2017. The demise of a model? The state of collective bargaining and worker representation in Germany. Economic and Industrial Democracy 38, 193–234.

Aguren, S., Edgren, J., 1980. New factories: job design through factory planning in Sweden. Stockholm: Swedish Employers Confederation.

Alchian, A.A., Demsetz, H., 1972. Production, information costs, and economic organization. American Economic Review 62, 777–795.

Aleksynska, M., 2018. Temporary employment, work quality, and job satisfaction. Journal of Comparative Economics 46, 722 – 735.

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

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

Arntz, M., Gregory, T., Zierahn, U., 2016. The risk of automation for jobs in OECD countries. OECD Social, Employment and Migration Working Papers 189.

Arntz, M., Gregory, T., Zierahn, U., 2017. Revisiting the risk of automation. Economics Letters 159, 157–160.

Autor, D.H., Dorn, D., 2013. The growth of low-skill service jobs and the polarization of the us labor market. American Economic Review 103, 1553–97.

Autor, D.H., Handel, M.J., 2013. Putting tasks to the test: Human capital, job tasks, and wages. Journal of Labor Economics 31, 59–96.

Baker, G.P., Hubbard, T.N., 2003. Make versus buy in trucking: Asset ownership, job design, and information. American Economic Review 93, 551–572.

Barca, F., Iwai, K., Pagano, U., Trento, S., et al., 1999. The divergence of the Italian and Japanese corporate governance models: the role of institutional shocks. Economic Systems 23, 35–60.

Barth, E., Bryson, A., Dale-Olsen, H., 2020. Union Density Effects on Productivity and Wages. Economic Journal 130, 1898–1936.

Barth, E., Moene, K.O., Willumsen, F., 2014. The scandinavian model—an interpretation. Journal of Public Economics 117, 60 – 72.

Bartling, B., Fehr, E., Schmidt, K.M., 2013. Jeea-fbbva lecture 2012: Use and abuse of authority: A behavioral foundation of the employment relation. Journal of the European Economic Association 11, 711–742.

Batstone, E., Gourlay, S., Levie, H., Moore, R., 1987. New Technology and the Process of Labour Regulation. Clarendon Press Oxford.

Battisti, M., Dustmann, C., Schönberg, U., 2020. Technological and organizational change and the careers of workers.

Belloc, F., Burdin, G., Landini, F., 2020a. Corporate Hierarchies and Labor Institutions. Department of Economics University of Siena 827. Department of Economics, University of Siena.

Belloc, F., Burdin, G., Landini, F., 2020b. Robots usage and worker voice: An empirical exploration. IZA Discussion Paper 13799.

Belloc, M., Pagano, U., 2009. Co-evolution of politics and corporate governance. International Review of Law and Economics 29, 106–114.

Belloc, M., Pagano, U., 2013. Politics-business co-evolution paths: workers' organization and capitalist concentration. International Review of Law and Economics 33, 23–36.

Ben-Ner, A., Kong, F., Lluis, S., 2012. Uncertainty, task environment, and organization design: An empirical investigation. Journal of Economic Behavior and Organization 82, 281–313.

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

Bolweg, J.F., 1976. Job design and industrial democracy. International Series on the Quality of Working Life Book 3.

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

Bowles, S., 1988. Capitalist technology: endogenous claim enforcement and the choice of technique. University of California, Berkeley - Working Paper .

Bowles, S., 2004. Microeconomics: Behavior, Institutions and Evolution. Princeton, NJ: Princeton University Press.

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

Brynjolfsson, E., Milgrom, P., 2013. Complementarity in organizations, in: Gibbons, R.S., Roberts, J. (Eds.), The Handbook of Organizational Economics. Princeton, NJ: Princeton University Press.

Carmichael, H.L., MacLeod, W.B., 1993. Multiskilling, technical change and the Japanese firm. Economic Journal 103, 142–160.

Cassar, L., Meier, S., 2018. Nonmonetary incentives and the implications of work as a source of meaning. Journal of Economic Perspectives 32, 215–38. URL: https://www.aeaweb.org/articles?id=10.1257/jep.32.3.215, doi:10.1257/jep.32.3.215.

Che, Y.K., Yoo, S.W., 2001. Optimal incentives for teams. American Economic Review 91, 525–541.

Coase, R.H., 1937. The nature of the firm. Economica 4, 386–405.

Cottini, E., Lucifora, C., 2013. Mental health and working conditions in europe. ILR Review 66, 958–988.

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

Deutsch, S., 1986. International experiences with technological change. Monthly Labor Review 109, 35–40.

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

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

Earle, J.S., Pagano, U., Lesi, M., 2006. Information technology, organizational form, and transition to the market. Journal of Economic Behavior & Organization 60, 471 – 489.

Freeman, R.B., Lazear, E.P., 1994. An economic analysis of works councils. NBER Working Paper No. 4918.

Freeman, R.B., Medoff, J.L., 1984. What do unions do. Industrial and Labor Relations Review 38, 244–263.

Frey, C.B., Osborne, M.A., 2017. The future of employment: How susceptible are jobs to computerisation? Technological Forecasting and Social Change 114, 254–280.

Genz, S., Bellmann, L., Matthes, B., 2019. Do German Works Councils Counter or Foster the Implementation of Digital Technologies? Journal of Economics and Statistics 239, 523–564.

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

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

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

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

Graversen, G., Lansbury, R., 1986. New Tecnologies and Industrial Relations in Scandinavia.

Greene, W.H., Hensher, D.A., 2010. Modeling Ordered Choices: A Primer. Cambridge University Press.

Hall, P.A., Gingerich, D.W., 2009. Varieties of capitalism and institutional complementarities in the macroeconomy: an empirical analysis. British Journal of Political Science 39, 449–482.

Hart, O., Moore, J., 1990. Property rights and the nature of the firm. Journal of Political Economy 98, 1119–1158.

Hogan, C., 2001. Enforcement of implicit employment contracts through unionization. Journal of Labor Economics 19.

Holmstrom, B., Milgrom, P., 1991. Multitask principal-agent analyses: Incentive contracts, asset ownership, and job design. Journal of Law, Economics and Organization 7, 24–52.

IFR, 2019. World Robotics 2019 Industrial Robots. Technical Report. International Federation of Robotics.

Itoh, H., 1994. Job design, delegation and cooperation: A principal-agent analysis. European Economic Review 38, 691–700.

Jirjahn, U., 2010. Works councils and employment growth in German establishments. Cambridge Journal of Economics 34, 475–500.

Katz, L., Krueger, A., 2019. The rise and nature of alternative work arrangements in the United States, 1995–2015. Industrial and Labor Relations Review 72, 382–416.

Landini, F., 2012. Technology, property rights and organizational diversity in the software industry. Structural Change and Economic Dynamics 23, 137 – 150.

Landini, F., 2013. Institutional change and information production. Journal of Institutional Economics 9, 257–284.

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

Lordan, G., Neumark, D., 2018. People versus machines: The impact of minimum wages on automatable jobs. Labour Economics 52, 40–53.

Malcomson, J.M., 1983. Trade unions and economic efficiency. Economic Journal 93, 51–65.

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

Martin, A., 1987. Unions, The Quality of Work, and Technological Change in Sweden. Temple University Press. pp. 95–139.

Milgrom, P.R., Roberts, J.D., 1992. Economics, Organization and Management. Englewood Cliffs, NJ: Prentice Hall.

Moene, K.O., Wallerstein, M., 2006. Social democracy as a development strategy, in: Bardhan, P., Bowles, S., Wallerstein, M. (Eds.), Globalization and Egalitarian Redistribution. Princeton: Princeton University Press, pp. 148–168.

Nedelkoska, L., Quintini, G., 2018. Automation, skills use and training. OECD Social, Employment and Migration Working Papers, No. 202, OECD Publishing, Paris .

Nikolova, M., Cnossen, F., 2020. What makes work meaningful and why economists should care about it. Labour Economics 65, 101847.

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

Pagano, U., Rowthorn, R., 1994. Ownership, technology and institutional stability. Structural Change and Economic Dynamics 5, 221–242.

Parolin, Z., 2020. Organized labor and the employment trajectories of workers in routine jobs: Evidence from US panel data. Brookings Institution .

Pouliakas, K., 2018. Determinants of automation risk in the EU labour market: a skills-needs approach. IZA Discussion Paper No. 11829.

Presidente, G., 2019. Institutions, Holdup and Automation. Technical Report.

Reich, M., Devine, J., 1981. The microeconomics of conflict and hierarchy in capitalist production. Review of Radical Political Economics 12, 27–45.

Rosner, M., Putterman, L., 1991. Factors behind the supply and demand for less alienating work, and some international illustrations. Journal of Economic Studies 18, 18–41.

Sampson, A.A., 1993. Bargaining over effort and the monitoring role of unions. European Journal of Political Economy 9, 371–381.

Sandberg, Å., Steen, A.G., Sandstrøm, L., Ullmark, P., 1992. Technological change and co-determination in Sweden. Philadelphia, PA: Temple University Press.

Savona, M., 2019. The Value of Data: Towards a Framework to Redistribute It. SPRU working paper 21.

Schöttner, A., 2008. Relational contracts, multitasking, and job design. Journal of Law, Economics, & Organization 24, 138–162.

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

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

Walker, M., 2020. Principles for effective automation in post-trade processing-Part 1: Beware the 'bot'army. Journal of Securities Operations & Custody 12, 320–335.

Wilkinson, B., 1983. The Shopfloor Politics of New Technology. Heinemann Educational Books.

Williamson, O.E., 1985. The Economic Institutions of Capitalism: Firms, Markets, Relational Contracting. New York, NY: Free Press.

Zolas, N., Kroff, Z., Brynjolfsson, E., McElheran, K., Beede, D.N., Buffington, C., Goldschlag, N., Foster, L., Dinlersoz, E., 2020. Advanced Technologies Adoption and Use by U.S. Firms: Evidence from the Annual Business Survey. Working Paper 28290. National Bureau of Economic Research.

Figures and Tables

Table 1: Payoff matrix.

	Worker (w)	
Owner (o)	With ER (G_H)	Without ER (G_L)
High automability (D_H)	$q\theta/r - s,\ s - \theta/r + \theta^2/2r^2 - c$	$q\theta/r - s,\ s - \theta/r + \theta^2/2r^2$
Low automability (D_L)	$q\lambda - s,\ s + \lambda^2/2 - c$	$-s,\ s$

Notes: Players' payoffs. For their derivation see Section A.1.1 in Appendix.

Table 2: Descriptive statistics.

Variable	Mean	Min.	Max.	Std. Dev.
Task features - the job involves:				
Dealing with people (from never to always)	4.143	1	7	2.445
Visiting customers or clients (1=yes, 0=no)	0.247	0	1	0.431
Solving unforeseen problems (1=yes, 0=no)	0.818	0	1	0.385
Monotonous tasks (1=yes, 0=no)	0.473	0	1	0.499
Complex tasks (1=yes, 0=no)	0.603	0	1	0.489
Learning new things (1=yes, 0=no)	0.724	0	1	0.446
Teamwork (1=yes, 0=no)	0.629	1	5	0.482
Applying own ideas (from never to always)	3.447	1	5	1.315
Influencing important decisions (from never to always)	3.035	1	5	1.298
Measures of automation risk				
Risk of automation [Model 1]	0.530	0.103	0.875	0.175
High risk of automation (Risk > 0.7) [Model 1]	0.194	0	1	0.395
FO's probability of automation (Frey and Osborne, 2017)	0.562	0.002	0.990	0.376
High FO's probability of automation (Probability > 0.7)	0.483	0	1	0.499
Employee representation				
ER	0.502	0	1	0.500
Control variables				
Female	0.480	0	1	0.499
Age	40.343	15	89	11.911
Education: primary	0.036	0	1	0.188
Education lower secondary	0.136	0	1	0.342
Education: upper secondary	0.423	0	1	0.494
Education: post-secondary	0.062	0	1	0.241
Education: tertiary	0.341	0	1	0.474
Firm size (1-9)	0.254	0	1	0.435
Firm size (10-249)	0.487	0	1	0.499
Firm size (250+)	0.248	0	1	0.432
Computer use (1=yes, 0=no)	0.562	0	1	0.496

Notes: Descriptive statistics are obtained over the EWCS data, 2010 and 2015 waves. Sample restricted to salaried workers. Task features are computed using the following survey questions: i) Dealing with people: "Does your main paid job involve... Dealing directly with people who are not employees at your workplace such as customers, passengers, pupils, patients, etc."; ii) Visiting customers or clients: "Does your work involve visiting customers, patients, clients or working at their premises or in their home?"; iii) Solving unforeseen problems: "Generally, does your main paid job involve... solving unforeseen problems on your own"; iv) Monotonous tasks: "Generally, does your main paid job involve... monotonous tasks"; v) Complex tasks: "Generally, does your main paid job involve... complex task"; vi) Learning new things: "Generally, does your main paid job involve... learning new things"; vii) Teamwork: "Do you work in a group or team that has common tasks and can plan its work?"; viii) Applying own ideas: in your job... "You are able to apply your own ideas in your work"; ix) Influencing important decisions: in your job..."You can influence decisions that are important for your work".

Table 3: Automation risk and ER: OLS estimates.

	(1) Risk of automation	(2) Risk of automation	(3) Risk of automation	(4) Risk of automation	(5) Risk of automation	(6) Risk of automation
ER	-0.090***	-0.040***	-0.042***	-0.024***	-0.023***	-0.022***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Female		0.024***	0.027***	0.044***	0.044***	0.040***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age		-0.006***	-0.006***	-0.006***	-0.006***	-0.006***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age^2		0.000***	0.000***	0.000***	0.000***	0.000***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lower-secondary edu.		-0.029***	-0.021***	-0.012***	-0.013***	-0.010***
		(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Upper-secondary edu.		-0.056***	-0.038***	-0.033***	-0.034***	-0.022***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Post-secondary edu.		-0.167***	-0.143***	-0.134***	-0.135***	-0.117***
		(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Tertiary edu.		-0.325***	-0.286***	-0.259***	-0.261***	-0.222***
		(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Firm size: 10-249			0.005***	0.007***	0.007***	0.006***
			(0.001)	(0.001)	(0.001)	(0.001)
Firm size: 250+			0.028***	0.024***	0.023***	0.022***
			(0.002)	(0.001)	(0.002)	(0.001)
Computer use			-0.061***	-0.054***	-0.055***	-0.037***
			(0.001)	(0.001)	(0.001)	(0.001)
Estimation	OLS	OLS	OLS	OLS	OLS	OLS
No. Obs.	45,779	45,693	45,289	44,893	44,893	44,847
R^2	0.065	0.610	0.635	0.706	0.708	0.732
Individual-level controls	No	Yes	Yes	Yes	Yes	Yes
Firm-level controls	No	No	Yes	Yes	Yes	Yes
Country effects	No	No	No	Yes	Yes	Yes
Year effects	No	No	No	Yes	Yes	Yes
Industry effects	No	No	No	Yes	Yes	Yes
Country×Year effects	No	No	No	No	Yes	Yes
Industry×Year effects	No	No	No	No	Yes	Yes
Occupation effects	No	No	No	No	No	Yes

Notes: Estimation by OLS on a pooled sample of individual-level observations. Risk of automation is computed as in Arntz et al. (2017) on EWCS data. Firm-level controls include firm size. Primary education is the benchmark category for the educational classes. Firm size of less than 10 employees is the benchmark category for the firm size classes. Some specifications include dummies for countries (34), industries (11) and occupations (10). Standard errors in parentheses are heteroschedasticity robust. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: High automation risk and ER: logit model estimates.

	(1) High risk of automation	(2) High risk of automation	(3) High risk of automation	(4) High risk of automation	(5) High risk of automation	(6) High risk of automation
ER	-0.109***	-0.047***	-0.061***	-0.036***	-0.034***	-0.035***
	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Female		0.054***	0.065***	0.091***	0.092***	0.087***
		(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Age		-0.009***	-0.009***	-0.012***	-0.011***	-0.011***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age^2		0.000***	0.000***	0.000***	0.000***	0.000***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lower-secondary edu.		-0.084***	-0.057***	-0.032***	-0.030**	-0.018*
		(0.013)	(0.012)	(0.012)	(0.012)	(0.010)
Upper-secondary edu.		-0.174***	-0.113***	-0.099***	-0.099***	-0.060***
		(0.012)	(0.011)	(0.011)	(0.011)	(0.010)
Post-secondary edu.		-0.390***	-0.312***	-0.279***	-0.280***	-0.227***
		(0.013)	(0.012)	(0.012)	(0.012)	(0.011)
Tertiary edu.		-0.455***	-0.377***	-0.343***	-0.344***	-0.291***
		(0.012)	(0.011)	(0.011)	(0.011)	(0.010)
Firm size: 10-249			0.047***	0.040***	0.040***	0.035***
			(0.004)	(0.004)	(0.004)	(0.004)
Firm size: 250+			0.092***	0.082***	0.080***	0.074***
			(0.005)	(0.005)	(0.005)	(0.005)
Computer use			-0.123***	-0.099***	-0.099***	-0.068***
			(0.003)	(0.003)	(0.003)	(0.004)
Estimation	Logit	Logit	Logit	Logit	Logit	Logit
No. Obs.	45,779	45,693	45,289	44,893	44,893	44,844
Individual-level controls	No	Yes	Yes	Yes	Yes	Yes
Firm-level controls	No	No	Yes	Yes	Yes	Yes
Country effects	No	No	No	Yes	Yes	Yes
Year effects	No	No	No	Yes	Yes	Yes
Industry effects	No	No	No	Yes	Yes	Yes
Country×Year effects	No	No	No	No	Yes	Yes
Industry×Year effects	No	No	No	No	Yes	Yes
Occupation effects	No	No	No	No	No	Yes

Notes: Estimation by logit on a pooled sample of individual-level observations. High risk of automation is computed as in Arntz et al. (2017) on EWCS data and coded as a dummy variable which equals 1 when the risk of automation is equal to or greater than 0.7. Firm-level controls include firm size. Primary education is the benchmark category for the educational classes. Firm size of less than 10 employees is the benchmark category for the firm size classes. Some specifications include dummies for countries (34), industries (11) and occupations (10). Marginal effects are displayed. Standard errors in parentheses are heteroschedasticity robust. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Automation risk and ER: comparison of different measures.

	(1)	(2)	(3)	(4)	(5)	(6)
	[Model 1]	[Model 2]	[Model 3]	[Model 1]	[Model 2]	[Model 3]
	Risk of automation	Risk of automation	Risk of automation	High risk of automation	High risk of automation	High risk of automation
ER	-0.022***	-0.017***	-0.002*	-0.035***	-0.022***	-0.006*
	(0.001)	(0.001)	(0.001)	(0.004)	(0.003)	(0.003)
Female	0.040***	0.043***	0.025***	0.087***	0.088***	0.043***
	(0.001)	(0.001)	(0.001)	(0.004)	(0.003)	(0.003)
Age	-0.006***	-0.003***	-0.002***	-0.011***	-0.006***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Age^2	0.000***	0.000***	0.000***	0.000***	0.000***	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lower-secondary edu.	-0.010***	-0.006***	-0.007**	-0.018*	-0.010	-0.009
	(0.003)	(0.002)	(0.003)	(0.010)	(0.009)	(0.007)
Upper-secondary edu.	-0.022***	-0.017***	-0.023***	-0.060***	-0.047***	-0.037***
	(0.002)	(0.002)	(0.003)	(0.010)	(0.009)	(0.007)
Post-secondary edu.	-0.117***	-0.120***	-0.032***	-0.227***	-0.223***	-0.048***
	(0.003)	(0.003)	(0.003)	(0.011)	(0.009)	(0.009)
Tertiary edu.	-0.222***	-0.225***	-0.041***	-0.291***	-0.274***	-0.067***
	(0.003)	(0.002)	(0.003)	(0.010)	(0.009)	(0.008)
Firm size: 10-249	0.006***	0.011***	0.021***	0.035***	0.043***	0.040***
	(0.001)	(0.001)	(0.001)	(0.004)	(0.003)	(0.003)
Firm size: 250+	0.022***	0.028***	0.034***	0.074***	0.077***	0.067***
	(0.001)	(0.001)	(0.002)	(0.005)	(0.005)	(0.005)
Computer use	-0.037***	-0.032***	-0.043***	-0.068***	-0.065***	-0.090***
	(0.001)	(0.001)	(0.001)	(0.004)	(0.003)	(0.004)
Estimation	OLS	OLS	OLS	Logit	Logit	Logit
No. Obs.	44,847	56,015	56,735	44,844	56,012	56,732
R^2	0.732	0.727	0.332			
Individual-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Country effects	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes
Country×Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Occupation effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Estimation on a pooled sample of individual-level observations. In Model 1, automation risk is computed as in Arntz et al. (2017), by including gender, age, education, sector, supervision responsabilities and income as controls. In Model 2, automation risk is computed as in Arntz et al. (2017), by including gender, age, education, sector and supervision responsabilities as controls (income is excluded). In Model 3, automation risk is computed as in Arntz et al. (2017), but additional controls for gender, age, education, sector, supervision responsabilities and income are all excluded. The high risk versions of the automation risk variables are dummies which equal 1 when the risk of automation is equal to or greater than 0.7. In all the regressions: firm-level controls include firm size; primary education is the benchmark category for the educational classes; firm size of less than 10 employees is the benchmark category for the firm size classes. All specifications include dummies for countries (34), industries (11) and occupations (10). Standard errors in parentheses are heteroschedasticity robust. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Automation risk and ER: recursive bivariate probit model.

	High risk of automation		ER	
	Coef.	Marginal effect	Coef.	Marginal effect
ER	-0.708***	-0,128***		
	(0.131)	(0.023)		
ER share by industry-country			1.885***	0.517
			(0.075)	(0.020)
ρ	0.254***			
	(0.080)			
No. Obs.	24866			
Wald test of $\rho = 0$	$\chi^2(1) = 9.171$	Prob>$\chi^2(1) = 0.003$		

Notes: Recursive bivariate probit estimates using individual-level observations from EWCS 2015. Controls include gender, age and education, firm size, occupation and country dummies. ρ is the correlation between the error terms of the two equations. Standard errors in parentheses are heteroschedasticity robust. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Automation risk and ER: controlling for robot density.

	(1) Risk of automation	(2) Risk of automation	(3) High risk of automation	(4) High risk of automation
ER	-0.020***	-0.021***	-0.025***	-0.028***
	(0.002)	(0.002)	(0.007)	(0.007)
Female	0.039***	0.040***	0.124***	0.123***
	(0.002)	(0.002)	(0.007)	(0.007)
Age	-0.005***	-0.005***	-0.013***	-0.013***
	(0.000)	(0.000)	(0.002)	(0.002)
Age^2	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Lower-secondary edu	-0.015***	-0.016***	-0.035**	-0.036**
	(0.004)	(0.004)	(0.018)	(0.018)
Upper-secondary edu	-0.025***	-0.026***	-0.065***	-0.064***
	(0.004)	(0.004)	(0.018)	(0.018)
Post-secondary edu	-0.120***	-0.121***	-0.262***	-0.264***
	(0.005)	(0.005)	(0.020)	(0.019)
Tertiary edu.	-0.243***	-0.242***	-0.343***	-0.341***
	(0.005)	(0.005)	(0.017)	(0.017)
Firm size: 10-249	0.018***	0.017***	0.055***	0.054***
	(0.002)	(0.002)	(0.007)	(0.007)
Firm size: 250+	0.047***	0.042***	0.109***	0.097***
	(0.003)	(0.003)	(0.010)	(0.010)
Computer use	-0.037***	-0.038***	-0.088***	-0.091***
	(0.002)	(0.002)	(0.008)	(0.008)
Robot density		0.001***		0.002***
		(0.000)		(0.000)
Estimation	OLS	OLS	Logit	Logit
Observations	13,952	13,906	13,952	13,906
R-squared	0.756	0.760		
Individual-level controls	Yes	Yes	Yes	Yes
Firm-level controls	Yes	Yes	Yes	Yes
Country effects	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes
Occupation effects	Yes	Yes	Yes	Yes

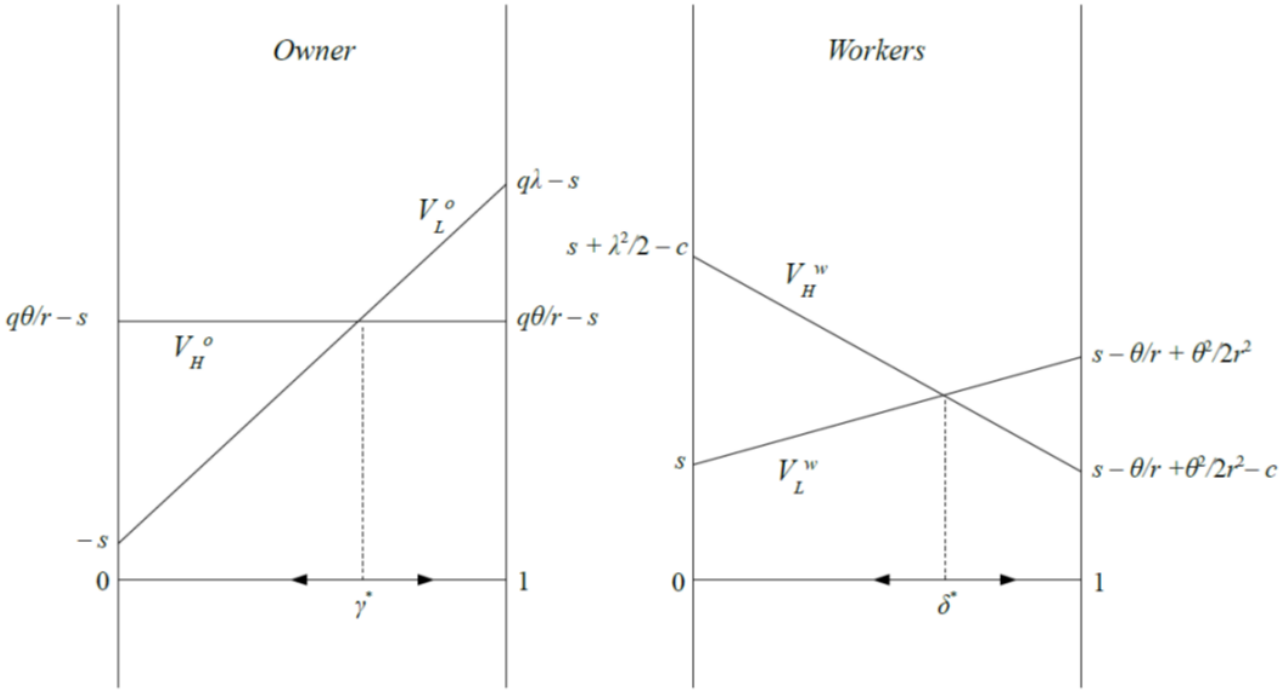
Notes: Estimation on a pooled sample of individual-level observations. Risk of automation is computed as in Arntz et al. (2017) on EWCS data. High risk of automation is a dummy variable which equals 1 when the risk of automation is equal to or greater than 0.7. Firm-level controls include firm size. Primary education is the benchmark category for the educational classes. Firm size of less than 10 employees is the benchmark category for the firm size classes. Marginal effects are displayed. All specifications include dummies for countries and occupations. Standard errors in parentheses are heteroschedasticity robust. *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Automation risk and ER: controlling for job insecurity and workplace reorganisation.

	(1) Risk of automation	(2) Risk of automation	(3) High risk of automation	(4) High risk of automation
ER	-0.022***	-0.021***	-0.035***	-0.031***
	(0.001)	(0.001)	(0.004)	(0.004)
Female	0.040***	0.040***	0.084***	0.082***
	(0.001)	(0.001)	(0.004)	(0.004)
Age	-0.006***	-0.005***	-0.011***	-0.011***
	(0.000)	(0.000)	(0.001)	(0.001)
Age^2	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Lower-secondary edu.	-0.008***	-0.008***	-0.011	-0.012
	(0.003)	(0.003)	(0.010)	(0.011)
Upper-secondary edu.	-0.021***	-0.020***	-0.051***	-0.052***
	(0.003)	(0.003)	(0.010)	(0.010)
Post-secondary edu.	-0.115***	-0.115***	-0.213***	-0.212***
	(0.003)	(0.003)	(0.011)	(0.011)
Tertiary edu.	-0.220***	-0.220***	-0.279***	-0.276***
	(0.003)	(0.003)	(0.010)	(0.010)
Firm size: 49-249	0.007***	0.007***	0.036***	0.037***
	(0.001)	(0.001)	(0.004)	(0.004)
Firm size: 250+	0.022***	0.024***	0.072***	0.075***
	(0.002)	(0.002)	(0.005)	(0.005)
Computer use	-0.036***	-0.035***	-0.067***	-0.064***
	(0.001)	(0.001)	(0.004)	(0.004)
Insecure job	0.023***	0.024***	0.046***	0.045***
	(0.001)	(0.001)	(0.004)	(0.004)
Workplace reorganization		-0.014***		-0.028***
		(0.001)		(0.004)
Estimation	OLS	OLS	Logit	Logit
No. Obs.	42,343	41,337	42,340	41,334
R^2	0.735	0.737		
Individual-level controls	Yes	Yes	Yes	Yes
Firm-level controls	Yes	Yes	Yes	Yes
Country effects	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes
Country×Year effects	Yes	Yes	Yes	Yes
Industry×Year effects	Yes	Yes	Yes	Yes
Occupation effects	Yes	Yes	Yes	Yes

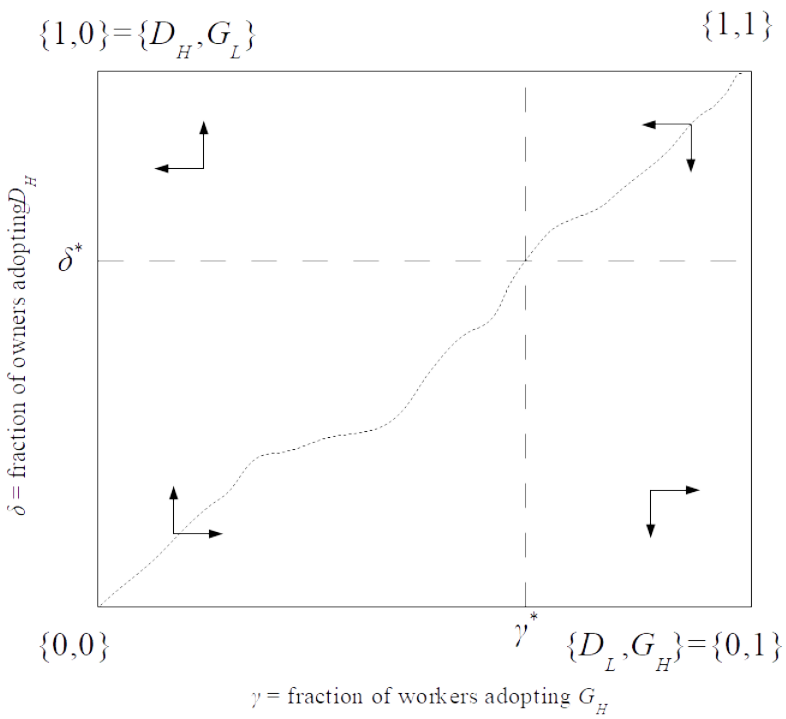
Notes: Estimation on a pooled sample of individual-level observations. Risk of automation is computed as in Arntz et al. (2017) on EWCS data. High risk of automation is computed as in Arntz et al. (2017) on EWCS data and coded as a dummy variable which equals 1 when the risk of automation is equal to or greater than 0.7. Firm-level controls include firm size. Primary education is the benchmark category for the educational classes. Firm size of less than 10 employees is the benchmark category for the firm size classes. All specifications include dummies for countries (34), industries (11) and occupations (10). Marginal effects are displayed. Standard errors in parentheses are heteroschedasticity robust. *** p<0.01, ** p<0.05, * p<0.1.

Figure 1: Expected payoffs to owner and workers.



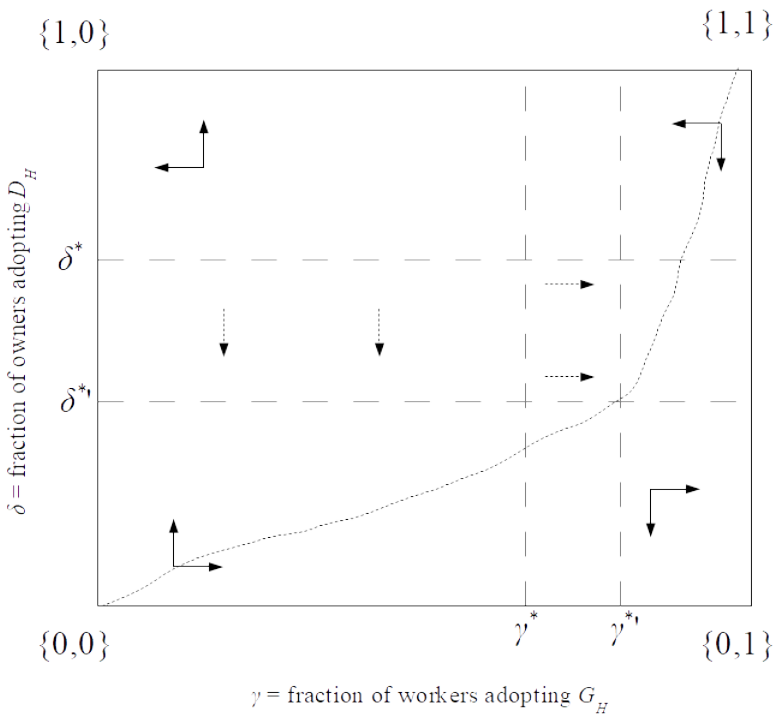
Notes: This figure displays the expected payoff functions; δ is the fraction of owners adopting D_H and γ is the fraction of workers adopting G_H. The vertical intercepts are from Table 1.

Figure 2: Asymptotically stable states and out-of-equilibrium dynamics.



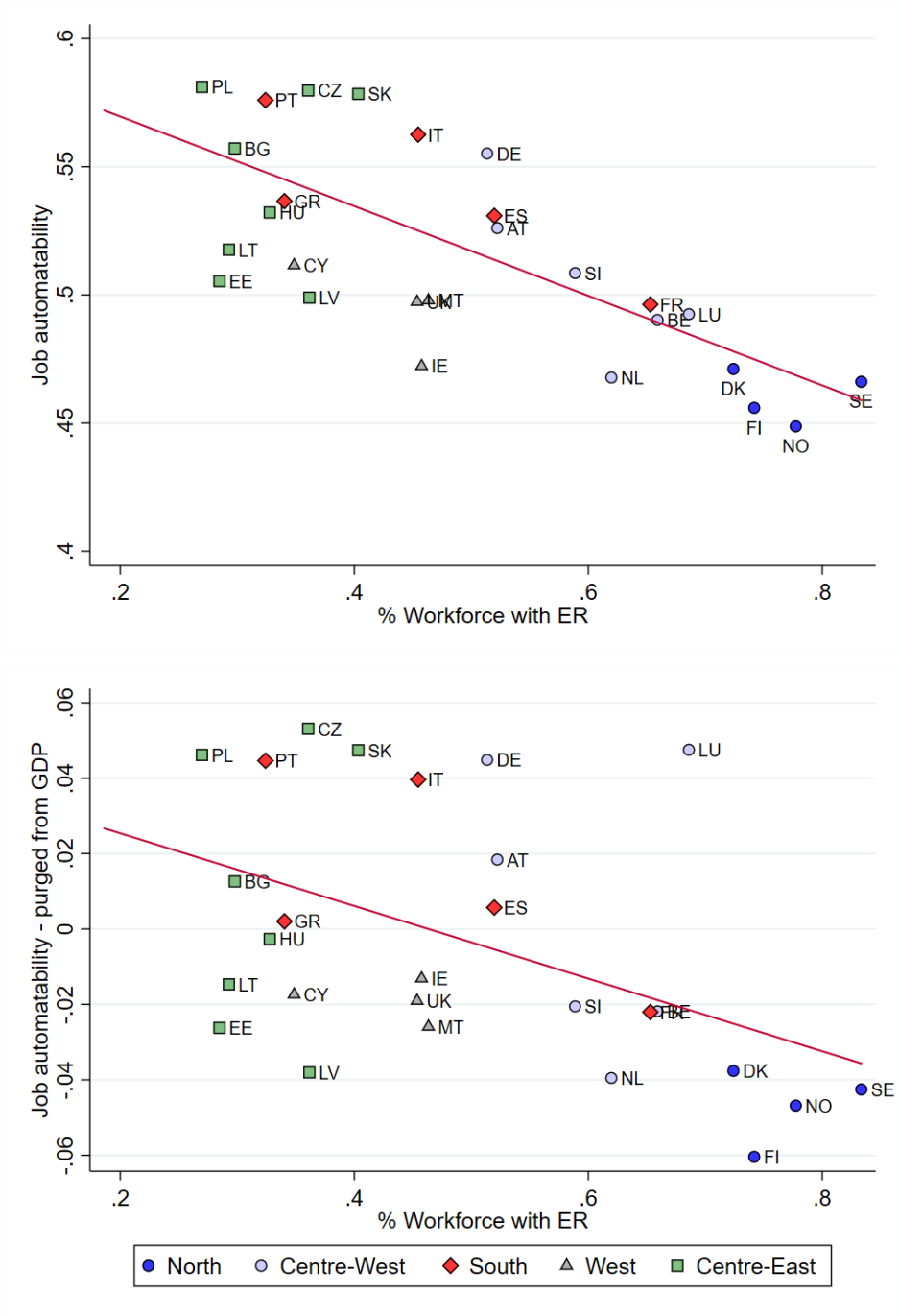
Notes: The arrows represent the disequilibrium adjustment in the number of owners (vertical movements) and workers (horizontal movements).

Figure 3: Changes in the basin of attraction.



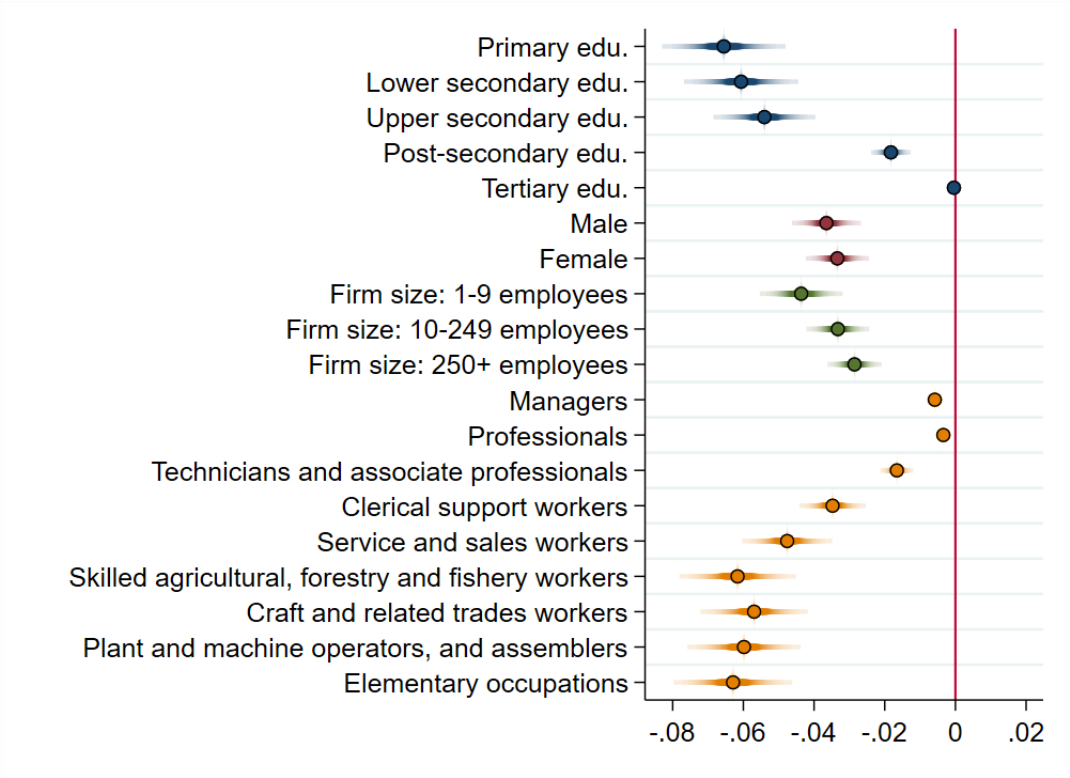
Notes: The figure shows the changes in the size of the basins of attraction when the cost of collective action c increases (δ^* reduces to $\delta^{*\prime}$) and probability of labour reinstatement r reduces (γ^* increases to $\gamma^{*\prime}$). With respect to γ^*, similar changes would obtain after an increase in the difference between net benefits in the present job and in the next best alternative θ. Overall, these changes make the relatively inefficient convention $\{1, 0\}$ more likely to emerge.

Figure 4: Correlation between share of ER and job automation risk.



Notes: The figures display the correlation between the share of workforce employed in workplaces with ER and our baseline measure of job automatability (computed as in Arntz et al. (2017)), both averaged at a country level using EWCS 2015 data. In the bottom panel, we use job automatability values purged from countries' GDP: these values are obtained as residuals from regressing our baseline measure of job automatability against countries' GDP per capita (in PPP). Countries were classified according to industrial relations regimes as proposed by Visser (2009).

Figure 5: Marginal effect of ER on job automation risk.



Notes: Conditional correlations between ER and high risk of automation, obtained from the logit model presented in column 6 of Table 4.

A.1 Theoretical Appendix

A.1.1 Payoffs in Table 1

Let us indicate with $u_w(D, G)$ the utility of a G-type worker when matched with a D-type owner, and with $u_o(D, G)$ the utility of a D-type owner when matched with a G-type worker, with $D = \{D_H, D_L\}$ and $G = \{G_H, G_L\}$. Moreover, let us write $e^*_w(i, j)$ as the best-response level of e for a i-type worker when matched with a j-type owner. Given Eq. (1) we have:

$$u_w(D_H, G_H) = s - e_w^2/2 - (1 - e_w)\theta/r - c \quad , \quad u_w(D_H, G_L) = s - e_w^2/2 - (1 - e_w)\theta/r \tag{A.1.1}$$

$$u_w(D_L, G_H) = s + \lambda e_W - e_w^2/2 - c \quad , \quad u_w(D_L, G_L) = s - e_w^2/2 \tag{A.1.2}$$

Moreover, given Remark 1, we have:

$$e^*_w(D_H, G_H) = e^*_w(D_H, G_L) = \theta/r \quad , \quad e^*_w(D_L, G_H) = \lambda \quad , \quad e^*_w(D_L, G_L) = 0 \tag{A.1.3}$$

By replacing effort levels from Eqs. (A.1.3) into Eqs. (A.1.1) and (A.1.2) as well as into o's utility from Eq. (2) we obtain the following results:

$$u_o(D_H, G_H) = u_o(D_H, G_L) = q\theta/r - s \ , \ u_o(D_L, G_H) = q\lambda - s \ , \ u_o(D_L, G_L) = -s \tag{A.1.4}$$

$$u_w(D_H, G_H) = s - \theta/r + \theta^2/2r^2 - c \quad , \quad u_w(D_H, G_L) = s - \theta/r + \theta^2/2r^2 \tag{A.1.5}$$

$$u_w(D_L, G_H) = s + \lambda^2/2 - c \quad , \quad u_w(D_L, G_L) = s \tag{A.1.6}$$

A.1.2 Proof of Proposition 1

In game Γ, D_H is always a best response to G_L and G_L is always a best response D_H. This implies that: i) $\{D_H, G_L\}$ is always a Nash equilibrium; and ii) $\{D_H, G_H\}$ and $\{D_L, G_L\}$ are never Nash Equilibria. Moreover, $\{D_L, G_H\}$ is a Nash equilibrium as long as: (a) $q\lambda - s > q\theta/r - s$ and (b) $s + \lambda^2/2 - c > s$. Condition (a) and (b) reduce to $r > \theta/\lambda = \bar{r}$ and $c < \lambda^2/2 = \bar{c}$. It follows that when $r > \bar{r}$ and $c < \bar{c}$ both $\{D_H, G_L\}$ and $\{D_L, G_H\}$ are Nash equilibria.

A.1.3 Proof of Proposition 2

Two necessary and sufficient conditions for $\{D_L, G_H\}$ to Pareto dominates $\{D_H, G_L\}$ is that $q\lambda - s > q\theta/r - s$ and $s + \lambda^2/2 - c > s - \theta/r + \theta^2/2r^2$, which reduces to a) $r > \theta/\lambda$ and b) $c < \lambda^2/2 + \theta/r - \theta^2/2r^{=}\bar{c} + \theta/r - \theta^2/2r^2$. Conditions a) and b), together with the results of Proposition 1, implies that when both $\{D_H, G_L\}$ and $\{D_L, G_H\}$ are Nash equilibria and $\theta/r < 2$, the former Pareto dominates the latter.

A.1.4 Proof of Proposition 3

The five organisational equilibria are derived by solving the system (7)-(8) for $\Delta\delta = 0$ and $\Delta\gamma = 0 = 0$. The proof in this case is omitted. The asymptotic properties of each equilibrium are derived by analysing the Jacobean Matrix $J(\delta, \gamma)$ associated to system (7)-(8), which takes the following form:

$$J = \begin{pmatrix} (1-2\delta)\alpha\beta\left(q\theta/r - \gamma q\lambda\right) & \delta(1-\delta)\alpha\beta\left(-q\lambda\right) \\ \\ \gamma(1-\gamma)\alpha\beta\left(-\dfrac{\lambda^2}{2}\right) & (1-2\gamma)\alpha\beta\left(\dfrac{\lambda^2}{2} - c - \delta\dfrac{\lambda^2}{2}\right) \end{pmatrix}$$

At $\{0, 0\}$, we have:

$$J = \begin{pmatrix} \alpha\beta q\theta/r & 0 \\ 0 & \alpha\beta\left(\dfrac{\lambda^2}{2} - c\right) \end{pmatrix}$$

from which it follows that

$$Tr(J) = \alpha\beta\left(q\theta/r + \frac{\lambda^2}{2} - c\right) \qquad , \qquad Det(J) = \alpha^2\beta^2 q\theta/r\left(\frac{\lambda^2}{2} - c\right) \tag{A.1.7}$$

Since Tr$(J) > 0$ and Det$(J) > 0$ for any $c < \lambda^2/2$, $\{0, 0\}$ is asymptotically unstable.

At $\{1, 0\}$, we have:

$$J = \begin{pmatrix} -\alpha\beta q\theta/r & 0 \\ 0 & -\alpha\beta c \end{pmatrix}$$

from which it follows that

$$Tr(J) = -\alpha\beta(q\theta/r + c) \qquad , \qquad Det(J) = \alpha^2\beta^2 cq\theta/r \tag{A.1.8}$$

Since Tr$(J) < 0$ and Det$(J) > 0$, $\{1, 0\}$ is asymptotically stable.

At $\{0, 1\}$, we have:

$$J = \begin{pmatrix} \alpha\beta q(\theta/r - \lambda) & 0 \\ 0 & -\alpha\beta\left(\dfrac{\lambda^2}{2} - c\right) \end{pmatrix}$$

from which it follows that

$$Tr(J) = \alpha\beta\left[q(\theta/r - \lambda) - \frac{\lambda^2}{2} + c\right] \quad , \quad Det(J) = -\alpha^2\beta^2 q(\theta/r - \lambda)\left(\frac{\lambda^2}{2} - c\right) \tag{A.1.9}$$

Since Tr$(J) < 0$ and Det$(J) > 0$ for any $r > \theta/\lambda$ and $c < \lambda^2/2$, $\{0, 1\}$ is asymptotically stable.

At $\{1, 1\}$, we have:

$$J = \begin{pmatrix} -\alpha\beta q(\theta/r - \lambda) & 0 \\ 0 & \alpha\beta c \end{pmatrix}$$

from which it follows that

$$Tr(J) = -\alpha\beta q(\theta/r - \lambda) + \alpha\beta c \quad , \quad Det(J) = -\alpha^2\beta^2 cq(\theta/r - \lambda) \tag{A.1.10}$$

Since Tr$(J) > 0$ and Det$(J) > 0$ for any $r > \theta/\lambda$, $\{1, 1\}$ is unstable.

At $\{\delta^*, \gamma^*\}$, we have:

$$J = \begin{pmatrix} 0 & \frac{\lambda^2 - 2c}{2}\left(1 - \frac{\lambda^2 - 2c}{2}\right)\alpha\beta(-q\lambda) \\ \frac{\theta}{\lambda r}\left(1 - \frac{\theta}{\lambda r}\right)\alpha\beta\left(-\frac{\lambda^2}{2}\right) & 0 \end{pmatrix}$$

from which it follows that

$$Det(J) = -\frac{\lambda^2 - 2c}{2}\left(1 - \frac{\lambda^2 - 2c}{2}\right)\alpha\beta(-q\lambda)\frac{\theta}{\lambda r}\left(1 - \frac{\theta}{\lambda r}\right)\alpha\beta\left(-\frac{\lambda^2}{2}\right) \tag{A.1.11}$$

Since Det$(J) < 0$ for any $r > \theta/\lambda$ and $c < \lambda^2/2$, $\{\delta^*, \gamma^*\}$ is a saddle.

A.1.5 Glossary of technical terms

In this section we provide a brief glossary of technical terms used in Section 2.2.

Asymptotic stability: property of an equilibrium $\{x, y\}$ such that small perturbations in the population composition will result in changes leading back to $\{x, y\}$.

Basin of attraction: it is defined as the set of initial states for which the unperturbed dynamical system moves toward the same equilibrium.

Corner solution: population composition such that in either group of agents the distribution of types is homogeneous, i.e. all workers and owners adopt the same strategy in their respective

set of strategy profiles.

Locus of states: set of all pairs $\{\delta, \gamma\}$ whose location satisfies some specific conditions, e.g. they define the border between two basins of attraction.

Vector field: it represents, for each state in the state space, the direction and velocity of change at the state.

A.2 Empirical Appendix

Table A.2.1: ER and workplace climate: worker motivation, manager-employee trust and co-operation.

	(1) High motivation	(2) High trust	(3) High cooperation
ER	0.014**	0.014***	0.029***
	(0.007)	(0.005)	(0.004)
Female	0.002	0.005	-0.006
	(0.006)	(0.005)	(0.004)
Age	-0.012***	-0.005***	-0.002**
	(0.002)	(0.001)	(0.001)
Age^2	0.000***	0.000***	0.000**
	(0.000)	(0.000)	(0.000)
Lower-secondary edu.	0.017	-0.002	0.023**
	(0.018)	(0.014)	(0.012)
Upper-secondary edu.	0.017	-0.001	0.020*
	(0.017)	(0.013)	(0.012)
Post-secondary edu.	0.010	-0.013	0.010
	(0.020)	(0.016)	(0.014)
Tertiary edu.	0.031*	-0.011	0.027**
	(0.018)	(0.014)	(0.012)
Firm size: 49-249	-0.053***	-0.047***	-0.024***
	(0.007)	(0.005)	(0.004)
Firm size: 250+	-0.104***	-0.086***	-0.035***
	(0.009)	(0.007)	(0.006)
Computer use	0.035***	-0.011*	-0.000
	(0.007)	(0.006)	(0.005)
Insecure job	-0.109***	-0.067***	-0.033***
	(0.007)	(0.005)	(0.004)
Estimation	Logit	Logit	Logit
Observations	28,843	28,606	28,268
Individual-level controls	Yes	Yes	Yes
Firm-level controls	Yes	Yes	Yes
Country effects	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes
Occupation effects	Yes	Yes	Yes

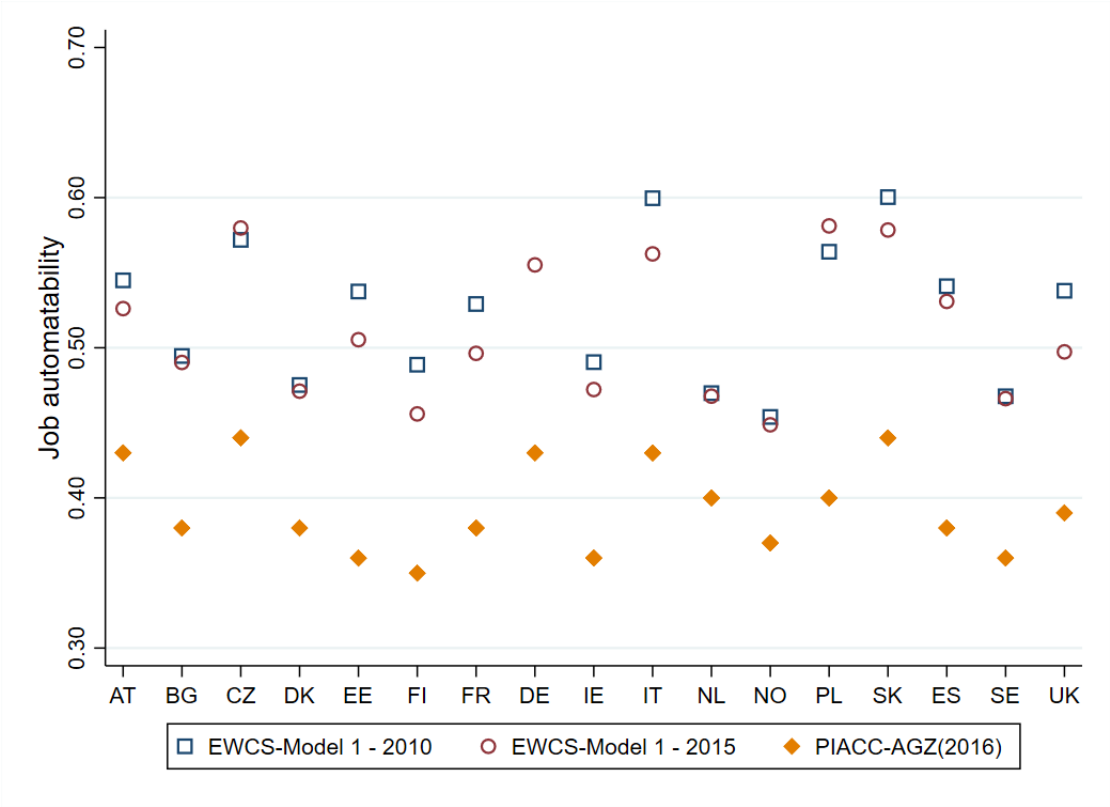
Notes: Estimation by OLS using individual-level observations from EWCS 2015. In Column (1), the dependent variable is a dummy that takes value 1 if respondents tend to agree or strongly agree with the following statement: *"The organisation I work for motivates me to give my best job performance"*. In Column (2), the dependent variable considers whether respondents tend to agree or strongly agree with the statement *"The management trusts the employees to do their work well"*. In column (3), the dependent variable takes value 1 if respondents agree with the statement *"There is good cooperation between you and your colleagues"*. Individual-level controls include gender, age, education, computer use at work and perceived job insecurity. Firm-level controls include firm size. Primary education is the benchmark category for the educational classes. All specifications include dummies for countries (34), industries (11) and occupations (10). Standard errors in parentheses are heteroschedasticity robust. *** p<0.01, ** p<0.05, * p<0.1.

Table A.2.2: Determinants of automation risk.

Task content	(1)
Dealing with people	-0.013***
	(0.001)
Visiting customers or clients	-0.078***
	(0.006)
Solving unforeseen problems	-0.015**
	(0.008)
Monotonous tasks	0.066***
	(0.005)
Complex tasks	-0.015**
	(0.006)
Learning new things	-0.012*
	(0.007)
Teamwork	-0.003
	(0.006)
Applying own ideas	-0.026***
	(0.003)
Influencing important decisions	-0.005*
	(0.002)

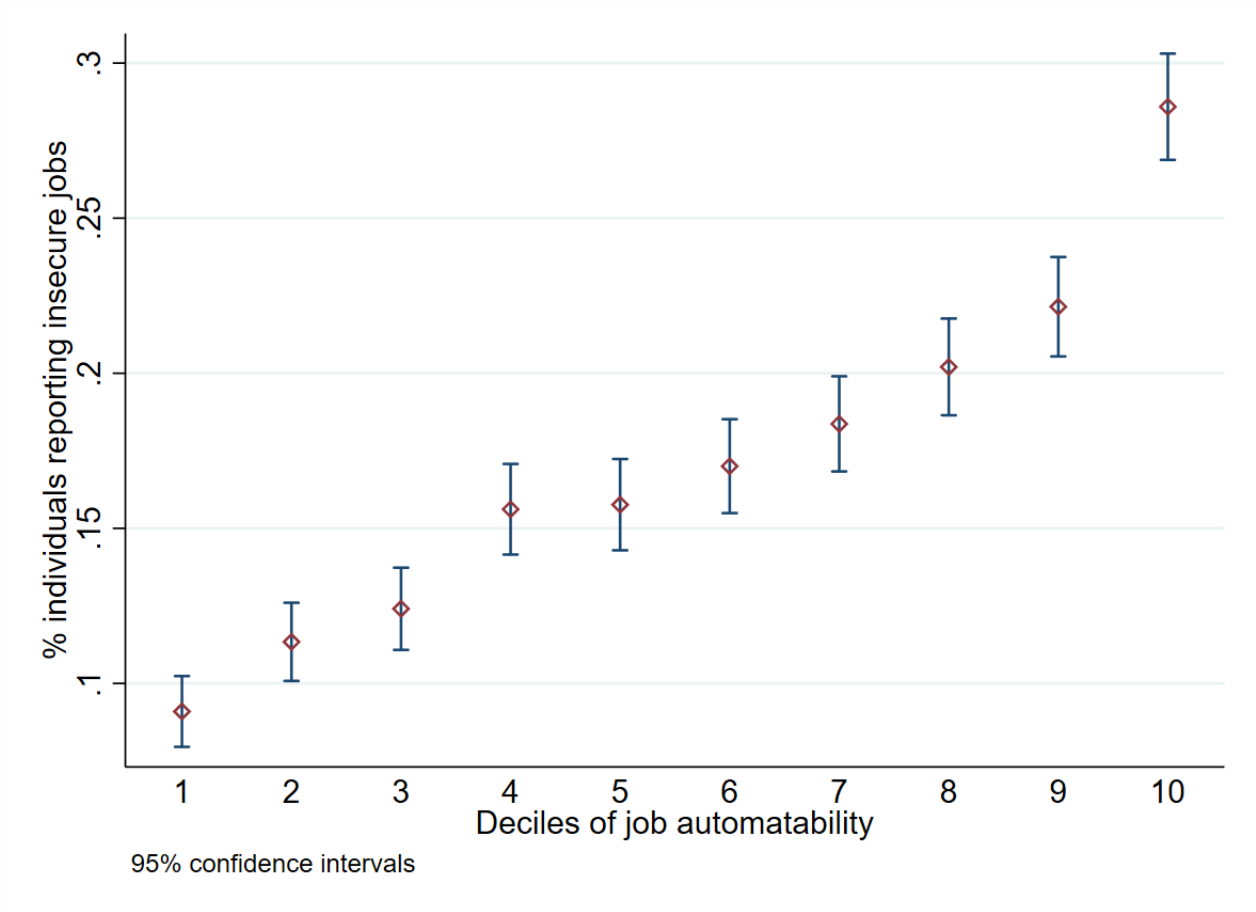
Notes: Marginal effects from the model explained in section 3.2. Using EWCS 2015, we regress Frey and Osborne's occupation-based automation risk scores on a set of self-reported characteristics reflecting the task content of inidviduals'job. Estimates also include gender gender, age, income, education, sector and supervision responsibilities. Sample restricted to salaried workers. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Figure A.2.1: Measures of job automation risk: comparison with Arntz et al. (2016).



Notes: Authors' calculations based on EWCS 2010-2015 as well as calculations reported in Arntz et al. (2016) for countries available in both PIAAC and EWCS.

Figure A.2.2: Correlation between subjective job insecurity and job automatability

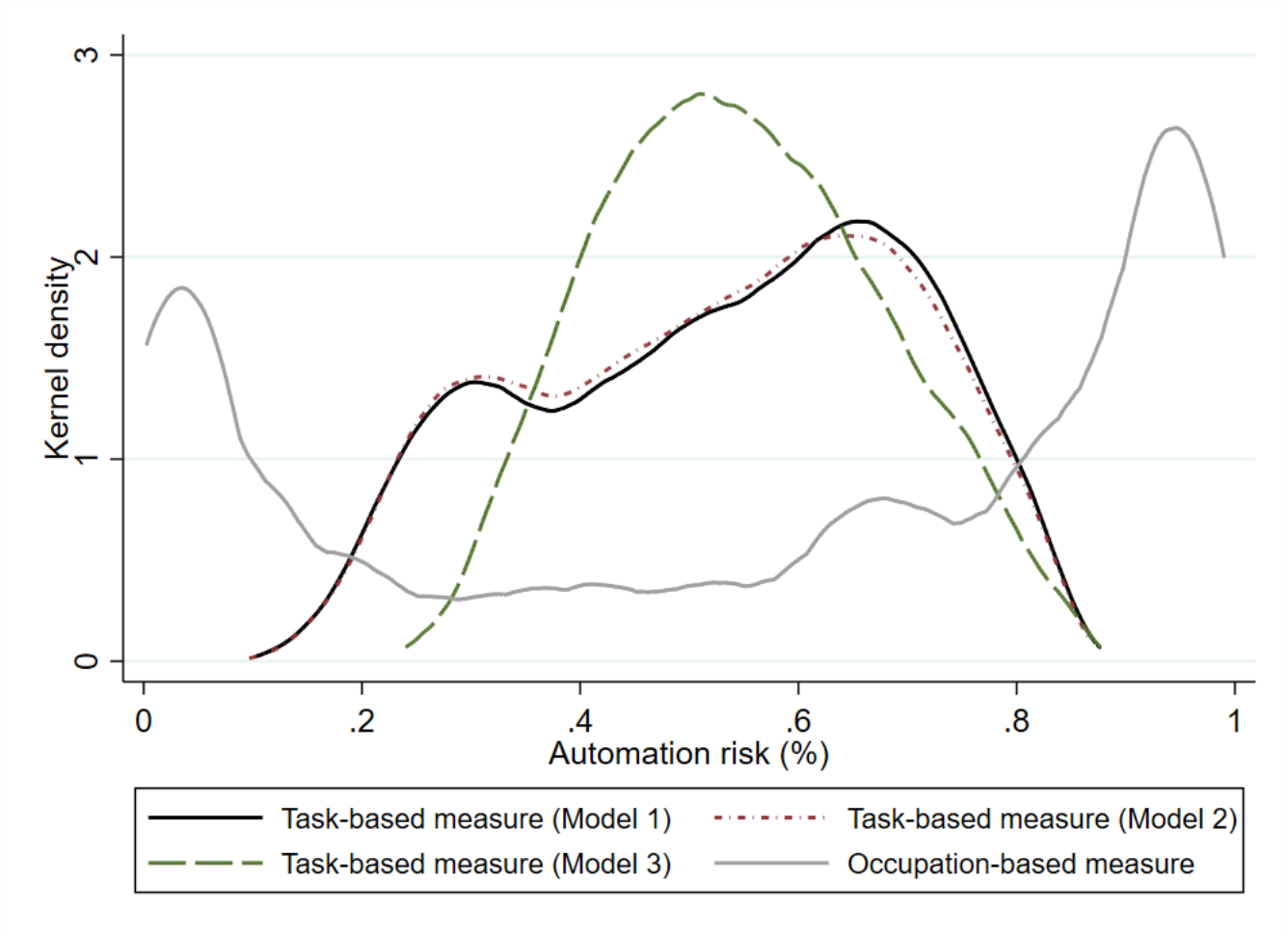


Notes: Authors' calculation based on EWCS 2015. Share of individuals reporting insecure jobs by deciles of job automatability. Subjective job insecurity: respondents tend to agree or strongly agree with the statement "I might lose my job in the next 6 months."

Figure A.2.3: Differences in task-related attributes by ER status

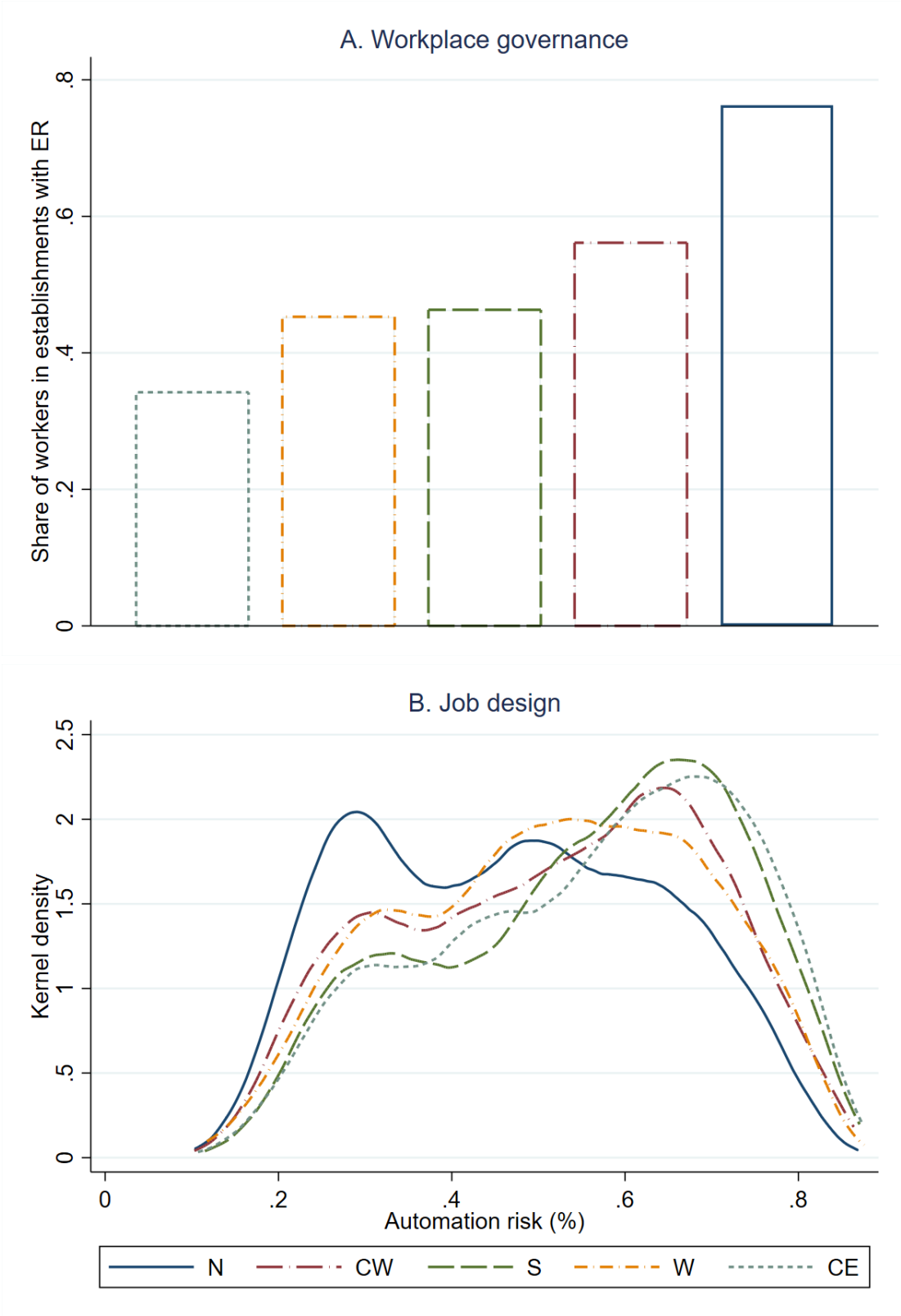
Notes: Authors' calculation based on EWCS 2015. Incidence of task-related attributes by individuals' workplace ER status.

Figure A.2.4: Distribution of automation risk: comparison of different measures.



Notes: Authors' calculation based on EWCS 2010-2015.

Figure A.2.5: Workplace governance and job designs by industrial relations regimes.



Notes: Authors' calculation based on EWCS 2010-2015. Countries were classified according to industrial relations regimes as proposed by Visser (2009). North (N): Denmark, Finland, Norway, Sweden; Centre-West (CW): Belgium, Germany, Luxembourg, Netherlands, Austria, Slovenia; South (S): Greece, Spain, France, Italy, Portugal; West (W): Ireland, Malta, Cyprus, UK; Centre-East (CE): Bulgaria, Czech Republic, Estonia, Latvia, Lithuania, Hungary, Poland, Romania, Slovakia. Panel A reports the share of workers in establishments where ER bodies are present. Panel B reports the kernel density function of automation risk.