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Coevolution of Job Automation Risk and Workplace Governance

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Abstract

In current debates about job automation, technology adoption is framed as a politics-neutral decision driven by the search for technical efficiency. Discussions about the nature of job design (i.e. the content and distribution of tasks within firms) and its associated automation risk are usually devoid of institutional context. However, job design may be affected by the way firms are governed. A critical feature of workplace governance is the extent to which decision making is shared by capital owners and workers via institutionalized forms of employee representation (ER). In this paper, we propose an evolutionary model to study the complementary fit and endogenous dynamics of job design and workplace governance. We show that two technological-political conventions are likely to emerge: in one of them 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. We explore the validity of the theory by using data from a large sample of European workers including detailed information on occupations, task environment, working conditions as well as presence of ER. Results are consistent with the theory: automation risk is negatively associated with the presence of ER. Our analysis can be useful to rationalize the historical experience of Nordic countries, where simultaneous experimentation with codetermination rights and job enrichment programs (supplemented by nationwide institutional reforms) seem to have had enduring consequences in the way these countries confront technological challenges. Policy debates about automation should avoid technological determinism and devote more attention to socio-institutional factors shaping the future of work.

Keywords: Automation, Job Design, Employee Representation, Evolutionary Game.

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1 Introduction

Industrial applications of artificial intelligence (AI) and robotic technology have significantly improved in the last decades. Rather than replicating the human mind, the most recent developments in the fields of neural networks, deep learning and algorithmic approach to unstructured data aim to single out tasks that can be easily (and cheaply) performed by robots. Such tasks are usually repetitive, highly routinized and require intensive information handling (Haenlein and Kaplan, 2019). This process is generally referred to as "automation", i.e. the adoption of technologies that enable some of the tasks previously performed by the worker to be produced by capital. The success of automation goes unquestioned: during the last three decades the per-worker number of installed industrial robots has increased by nearly four times both in US and Europe (Acemoglu and Restrepo, 2020a). At the same time, this wave of automation has originated deep concerns about its potential implications for labor displacement. Workers involved in tasks at high risk of automation are indeed likely to loose their job at some point in the future, with negative consequences in terms of both inequality and unemployment (Brynjolfsson and McAfee, 2014; Autor, 2015; Ford, 2015; Susskind and Susskind, 2015; Goos, 2014).

In this paper we focus on one particular feature of automation, namely job automation risk, i.e. the extent to which the tasks bundled into a job are likely to be automatized. While the prevailing view is that job automation risk is a given characteristic of the production process, we argue that it is also a matter of organizational choice, being it driven by a wide range of socio-institutional factors, such as managerial decisions, skill availability and industrial relations considerations (Arntz et al., 2016; Spencer and Slater, 2020). In particular, it is often overlooked the fact that job design and task composition are the outcomes of the strategic interactions that involve workers and capital owners at the workplace level. As a result, they can hardly be framed as the consequences of politics-free decisions, driven only by considerations of technical efficiency. Indeed, recent economic scholarship recognises that not all technologies which substitute away workers employed in automatable tasks are efficiency enhancing. Acemoglu and Restrepo (2019), for instance, list several examples of "so-so technologies" that replace workers but generate little productivity improvements.[1]

Our main aim is to deepen the analysis of the organizational 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 authority and decisions 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 organization and

[1] This includes machines such as self-checkout kiosks, self-service pumps in gasoline stations and other automated devices facilitating customer-employee substitution (Basker et al., 2017).

employment-related issues at the workplace level (e.g. unions, works councils, consultative committees). Formal employee representation has a long tradition in European countries. While wage negotiations are carried out by trade unions at the national, sectoral or firm levels, workplace employee representation deals with employment-related matters such as major organizational changes, training, working time and other working conditions (Forth et al., 2017). The main questions that motivate our study are thus the following: does ER affect firm's decisions affecting job design and hence also workers' exposure to the risk of automation? What are the implications of the link between ER and job automation risk for the design of labor market institutions and workplace governance?

We develop a theoretical framework where we study the relationship between job automation risk and workplace governance using an evolutionary model. We frame our argument with reference to two main research traditions. The first one is the so-called Radical school, which treats technological choices as socially determined (Gintis, 1976; Braverman, 1974; Bowles, 1985; Skillman, 1988; Pagano, 1991). The second one is 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. On this basis, we suggest that in the presence of asymmetric information and incomplete contracts firm-level choices about job design and workplace governance are driven by a two-ways causality: on the one hand, job designs characterized by higher (lower) automation risk makes the creation of ER bodies less (more) likely, because workers have smaller (larger) incentives to organize and demand voice channels. On the other, the absence (existence) of ER bodies makes automation-prone job designs more (less) probable, because employers find it more (less) convenient to extract work effort via labor discipline (i.e. involving employees in repetitive, routinized and easy to monitor tasks) than via institutionalized commitment (i.e. negotiating and enforcing a group-level effort norm). These two directions of causation imply that job design and workplace governance are institutional complements (Aoki, 2001) and multiple job design-workplace governance equilibria may exist. In particular, we show that two opposite technological-political conventions are likely to emerge: in one of them, workplace governance is based on ER and job designs are characterized by low automation risk; in the other, ER bodies are absent and workers are involved in automation-prone production tasks. Under certain conditions the former convention Pareto dominates the latter, which can nonetheless emerge as sub-optimal stable equilibrium. In our framework, the combination of contracting imperfections and conflicting interests within labor relationships may drive a wedge between private and social benefits of certain job design configurations, exposing workers to an inefficiently high automation risk.

We test these predictions using unique individual-level data from the 2010 and 2015 waves of the European Working Condition Survey (EWCS), covering nearly 44000 workers (in each wave) located in 35 European countries and providing 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. We exploit the information about ISCO occupational codes and proxies of task dimensions available in the EWCS to compute an individual-level measure of automation risk (Frey and Osborne, 2017; Arntz et al., 2017; Nedelkoska and Quintini, 2018; Pouliakas, 2018; Costinot et al., 2011; Barbieri et al., 2020). This structure of the data allows us to investigate the extent to which the presence of ER effectively relates with the risk of automation.

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 task content information provided 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. 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. These results hold both at an individual-level and in a country-industry fixed effects panel model. Regressions based on alternative proxies of automation risk, such as an index of job routineness à la Costinot et al. (2011) and the original occupation-based measure of automation risk computed by Frey and Osborne (2017), produce substantially similar results. Our evolutionary framework and documented empirical correlations appear to be consistent 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.

Our work is most closely related to two main streams of literature. First, we contribute to the studies on the determinants of job automation risk (Frey and Osborne, 2017; Arntz et al., 2017; Nedelkoska and Quintini, 2018). Interestingly, Arntz et al. (2017) show that cross-country differences in industry, occupational and educational structures explain only a small part of the variance in job automation risk. They suggest that differences in workplace organization can explain why some workers perform fewer automatable tasks than others even within narrowly defined industry and occupational groups. In this paper we provide a potential explanation for such within-industry and within-occupational heterogeneity based on the existence of shop-floor ER. When ER is present, the strategic interaction between workers and capital owners favour 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, the paper adds to an emerging literature focused on the role of labor market institutions in shaping the nature, pace and consequences of technological change. Previous research has focused on the effects of unemployment insurance and minimum wage laws on labor market outcomes of individuals exposed to automation (Lordan and Neumark, 2018; Bessen et al., 2019). In the US context, Parolin (2020) investigates the effect of union membership in shaping job stability and transitions of workers employed in routine jobs. Genz et al. (2019) analyze the effect of works councils on the implementation of digital technologies in German establishments. Using a large sample of European workers, our paper documents how job automation risk varies depending on the presence of ER at the workplace level. Despite the relevance of job design and task content for the debates about automation, their dependence on different forms of shop-floor ER, a rather distinct European labor institution granting workers a voice on work organization, has been seldom taken up by the previous literature. This, instead, is the primary aim of our paper. We claim that the social organization of the workplace affects the distribution of tasks at risk of being automated and thus shapes the pace of technology adoption.

The remaining parts of the paper are organized as follows. Section 2 presents the theoretical framework and develops a simple model of job design and workplace governance co-evolution. 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 as additional evidence in support of our theory. Finally, Section 6 concludes the paper with a discussion of policy implications.

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, represents the job of the worker. Firms define the task environment workers are involved in and bundle tasks into jobs (job design). The characteristics of such tasks 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). The extent to which the tasks bundled into a job can be performed by computer-controlled equipment affects the exposure of workers to automation risk. Usually, the latter is higher in presence of poorer job designs. In general, a job design characterized by high automation risk is a prerequisite for automation to actually take place.

We argue that the nature of job design cannot be understood in isolation from other aspects of the firm governance and organizational structure. Specifically, we emphasize the importance of a particular dimension of workplace governance: the extent to which employees are informed, consulted and share decision rights with capital owners via institutionalized ER channels. 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 side – fit together complementarily and reinforce each other.[2] Previous literature offers several insights to understand why automation risk and workplace governance may influence each other. But these mutual influences may be difficult to disentangle and have never been tackled directly in a unified framework.

2.1.1 Job design affects 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 right incentives to motivate workers to perform their duties. Employers may also require workers to make firm-specific investments in skills that are highly valuable in the context of the current relationship. This exposes workers to the hazard of opportunistic behaviour because the acquired skills have little or no value in alternative transactions. A central tenet in the new institutional view of the firm is that property rights and workplace governance would accommodate to provide an efficient solution to these problems, minimizing transaction costs and protecting quasi-rents associated with investments in specific assets (Alchian and Demsetz, 1972; Williamson, 1985). Therefore, if work effort is hard to monitor and investments in firm-specific human capital play a critical role, 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 labor.

When applied to automation, the new institutional view of the firm has interesting implications for the structure of workplace governance. As argued above, the adoption of automation technologies is easier in presence of poor job designs, because such designs are characterized by high routineness and low task complexity. In this type of job environment, workers are exposed to high automation risk. Moreover, 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

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

the need to device a workplace governance structure 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, in fact, 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 an automation prone job design is selected, workers have little incentives to organize themselves and to demand employee voice channels. Due to the nature of job design, workers have no gain other than their monetary compensation (i.e. wage) and by restraining from participation in firm governance they can at least save on the collective action costs needed to establish ER bodies. 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. Hence, the risk of substitution of labor with capital affects the structure of the human relations within the firm, alters the outside options of the workers and ultimately modifies the bargaining powers and the distribution of ownership rights.[3]

2.1.2 Workplace governance shapes job design and automation risk

However, the adoption of a certain job design does not occur in an institutional vacuum. Symmetrically, it is hard to exclude that the pre-existing structure of the workplace governance is neutral to the process of defining the automation risk. In an incomplete contract environment, firm owners manipulate job design on strategic grounds and depending on the nature of firm governance they can adopt different solutions.[4] When ER is absent, for instance, owners can benefit from selecting a job design that gradually transforms labor into an easy to monitor and general purpose input, as the latter improve their bargaining position vis-à-vis workers and improve 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 recognition of the fact that causality may be reversed, with ownership relations and workplace politics exerting an influence on job design, dates back to the early contri-

[3]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 labor, 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.

[4]An extensive literature in organizational economics analyzes 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 incentive considerations it may be optimal for employers to reduce task variety and group tasks according to their ease of monitoring (Milgrom and Roberts, 1992).

butions of the Radical economists (Gintis, 1976; Braverman, 1974; Marglin, 1974; Bowles, 1985; Duda and Fehr, 1987; Bartling et al., 2013). According to the radical theory of the firm, the conflict of interests over effort provision between firm owners and workers may induce the former to exercise authority in inefficient ways. Within this framework, the choice of job design is dictated by bargaining power considerations as well as technical efficiency. In particular, owners may have an incentive to replace difficult to monitor with easy to monitor labor and to adapt the job design to general-purpose and easily replaceable competencies (deskilling), increasing the credibility of the threat of dismissal for workers. In the case of automation, this process implies that the adoption of an automation-prone job design can be driven by labor discipline considerations and not only technical opportunities, with the consequence that the resulting size of automation risk can be higher than its socially desirable level. Interestingly, the fact that firms may implement profitable but technically inefficient job designs and technologies is somewhat recognised in contemporary scholarly work on automation. This is the case of the "so-so technologies", discussed by Acemoglu and Restrepo (2019), that displace labor, but generate negligible productivity gains. According to Acemoglu and Restrepo (2019), "excessive automation" may be driven by imperfections in the labor market. Indeed, the problem of effort extraction at the workplace level analysed by the Radical school can be seen as a particular mechanism within a broader family of theories of labor market failures.

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 thorugh 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 extract work effort compared to labor discipline devices (e.g. deskilling). For instance, unions may collect private information on workers' performance and facilitate peer-monitoring, alleviating the free-rider problem in team production under collective agreements (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).[5] 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.[6] Overall, shared workplace

[5]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.

[6]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

governance structures channelling employee voice and restricting the ability of owners to act unilaterally may reduce the costs of managing difficult-to-monitor labor for the firm, removing perverse incentives for implementing job designs characterized by suboptimally high levels of automation risk.[7]

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

The two views entailing 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. This refers 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 "organizational equilibria". On the one had, the existence of shared firm governance offers the possibility to rely on institutionalized commitment as a substitute for labor discipline to extract work effort, increasing owners' incentives to select richer and less automation-prone job designs. This choice is reinforced by the workers' willingness to establish ER as the intrinsic motivations associated with the richer task environment more than compensate the cost of collective organization. As a result, this particular organizational equilibrium can sustain itself. On the other hand, also an alternative organizational equilibrium is possible. In the absence of ER, automation-prone job designs are suitable alternatives to extract work effort via labor discipline. At the same time, this type of job designs creates little incentives for workers to organize via ER. It follows the cumulative causation between job design and workplace governance may lead to a completely different equilibrium configuration where high automation risk and the lack of ER complement each other.

While the emergence of multiple organizational equilibria has been already modelled in the literature,[8] to the best of our knowledge the application of this analytical

incentives and peer sanctions.

[7]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.

[8]Pagano and Rowthorn (1994) develops one of the first formalization of organizational equilibria comparing capitalists and worker-managed firms. (Landini, 2012, 2013) uses a similar approach to model

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 organization depends on two domains: job design (D) and workplace governance (G). Agents o choose in domain D and have two alternatives: high (D_H) and low (D_L) automation risk. D_H (D_L) is characterized by a poor (rich) task environment with a relatively large (small) share of repetitive, routine, easy to monitor tasks. Agents w choose in domain G and have two alternatives too: with (G_H) and without (G_L) ER. G_H (G_L) is associated with the presence (absence) of ER, e.g. unions, work councils, consultative committees.

Agents o e 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; and labor discipline, i.e. workers can be induced via job design to exert higher effort under the threat of their contract being terminated.[9] Labor discipline is higher in job designs characterized by repetitive and routine tasks, which make shirking easier to be detected. Moreover, we assume that workers earn a fixed wage and sustain a collective

organizational diversity in knowledge-intensive industries, such as software. Barca et al. (1999) and (Earle et al., 2006) provide empirical evidence supporting the view of organizational equilibria as a suitable concept to study the heterogeneity of corporate governance models.

[9]In a more complex setting we ought to account for the fact that effort extraction via institutionalized commitment is more difficult in presence of conflicting labor relations. For the sake of simplicity we leave this aspect out of the model under the assumption that in these circumstances effort extraction will take place primarily via labor discipline. This, together with the fact that over-time the threat of automation induces workers to de-organize, implies that the complementarity between job design and workplace governance is preserved even in presence of high conflict.

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

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

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 $m(D_H, G_L) = m(D_H, G_H)$ $= m(D_L, G_L) = 0$, $e_w^2/2$ is the convex cost of effort,[10] $a(D)$ is the easiness of effort monitoring, with $a(D_H) = 1$ and $a(D_L) = 0$, θ (>0) is the cost of job termination[11] (and $\lambda > \theta$), and $c(G)$ is the cost of collective action, with $c(G_H) = c > 0$ and $c(G_L) = 0$.

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 $e_w^*(D,G) = \lambda m(D,G) + a(D)\theta$, where $\lambda m(D,G)$ captures effort exertion via institutionalized commitment and $a(D)\theta$ effort exertion via labor discipline.*

Agents o's utility depends on two components: economic return and expected cost of automation. The former is defined as baseline sale returns, which depends positively on worker effort, net of wages. The latter is assumed to be positive in presence of a job design characterized by high automation risk and zero otherwise, because of the related expected investment in machines. Hence, we write the o's utility as follows:

$$u_o(D,G) = qe_w - s - k(D) \quad (2)$$

where $q(>0)$ is the value of output per unit of work done and $k(D)$ is the expected cost of automation, with $k(D_H) = k > 0$ and $k(D_L) = 0$.

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 palyers' 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*

[10] 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.

[11] The cost of job termination represents the difference between the net benefit that the worker obtains in the present job and the net benefit in next best alternative, which is exogenous to the firm. The value of the next best alternative will generally depends on the expected duration of the spell of unemployment following job termination, the level of reemployment salary relative to the current one, the existence government sponsored social incomes and the like. See Bowles (1988).

players o and w, respectively.

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: *Suppose $\lambda > \theta$. Then, there exist two values $\bar{k} = q\theta$ and $\bar{c} = \lambda^2/2$ such that: i) if $k > \bar{k}$ and $c > \bar{c}$, then $\{D_L, G_L\}$ is the only design-governance equilibrium;; ii) if $k < \bar{k}$ and $c > \bar{c}$, then $\{D_H, G_L\}$ is the only design-governance equilibrium; iii) if $k > \bar{k}$ and $c < \bar{c}$, then $\{D_L, G_H\}$ is the only design-governance equilibrium; iv) if $k < \bar{k}$ 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 a technological-political 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 expected cost of automation k and the cost of collective action c. When the latter are excessively large, D_L and G_L are dominant strategies and $\{D_L, G_L\}$ is the unique convention. If k is sufficiently small and c is large, effort extraction via labor discipline becomes a relatively convenient strategy, provided the high cost of establishing ER makes the alternative of institutionalized commitment not viable. Therefore, the unique technological-political convention is $\{D_H, G_L\}$. The opposite result obtains if c is sufficiently small and k is large. In this case, workers find it convenient to support the cost of collective action and commit to higher effort in presence of richer job design, while for owners the adoption of automation-prone job design is too costly. Therefore, the only technological-political convention is $\{D_L, G_H\}$. Finally, if both k and c are small, job design and workplace governance exhibit complementarities: for workers to establish ER is the best option when owners select a richer job design, because the intrinsic benefit associated with effort commitment more than compensate the cost of collective action. This is not the case when owners select a poor job design and the best response is not to establish ER. Similarly, for owners to rely on effort extraction via institutionalized commitment is the best solution when ER is present, because they can save on the expected cost of automation. This is not the case, however, when ER is absent, as the low expected cost of automation makes labor discipline a viable alternative. As a result, two technological-political conventions exist, namely $\{D_H, G_L\}$ and $\{D_L, G_H\}$.

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

Proposition 2: *Suppose $\lambda > \theta$, $k < \bar{k}$ and $c < \bar{c}$. If θ is sufficiently low, then the technological-political 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 effort commitment and the cost of collective action. If effort under institutionalized commitment is sufficiently large (i.e. $\lambda > \theta$), o's is always better-off under $\{D_L, G_H\}$ than under $\{D_H, G_L\}$, because in the former he can save on the expected cost of automation. In this sense, institutionalized commitment represents a more profitable strategy of effort extraction compared to labor discipline. With respect to w, if the cost of job termination θ is low enough, 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, 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 $\{D_H, G_L\}$.

2.2.2 Dynamics

To provide a framework for studying asymptotic stability we restrict the analysis to the space of parameter in which two technological-political conventions exist and introduce an explicit model of the dynamics of change. We consider a stylized process of interactions with no *a priori* social structure. Extensions looking at how richer characterizations of the social structure (e.g. local interactions and network topologies) are left to future research. In terms of behavioural decision rules, we rely on empirically (mostly experimentally) grounded assumptions in which agents update their beliefs by trial-and-error methods using local knowledge based on their and others recent past experience (Bowles, 2004).

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:

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

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

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

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

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

These expected payoff functions are illustrated in Figure 1.

To model the co-evolution of technology and workplace politics, suppose that both o and w update job design and workplace governance 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 ha a greater payoff, switches to B's degree of concentration 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 technological-political equilibria of the industry.

Proposition 3: *Suppose that $k < \bar{k}$ and $c < \bar{c}$. Then, the dynamical system composed of equations (7) and (8) is characterized by five technological-political equilibria:* $\{0, 0\}$,

$\{0,1\}$, $\{1,0\}$, $\{1,1\}$ and $\{\delta^*,\gamma^*\}$, with

$$\delta^* = \frac{\lambda^2 - 2c}{\lambda^2} \tag{9}$$

$$\gamma^* = \frac{q\theta - k}{q\lambda} \tag{10}$$

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 technological-political convention characterized by high automation risk and no ER. Analogous reasoning holds for states $\delta < \delta^*$ and $\gamma > \gamma^*$, where the industry converges to $\{0,1\}$. In this case, the stable state corresponds to a technological-political 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 locum transiting to $\{1,0\}$ and above 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 dynamics 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 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 technological-political 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 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 technological-political convention of the industry. On this respect, it is important to notice that $\partial\delta^*/\partial c < 0$, $\partial\gamma^*/\partial\theta > 0$ and $\partial\gamma^*/\partial k < 0$ imply that, increases in the cost of collective action c and the cost of job termination θ and reductions in the expected costs of automation k make the Pareto inefficient convention $\{1, 0\}$ more likely to emerge (see Figure 3).

3 Data and variables

3.1 The European Working Condition Survey: overview

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 job automation risk. Hence, as a first step of our empirical strategy, we need to measure job automation risk in a way that accounts for the variation in individual task content within occupations.

We tackle this issue by computing a measure of automation risk at the job-level, based 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 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., Costinot et al., 2011; 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.[12] The last waves also

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

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 (age, gender, education, occupation, firm size, industry).

Our final sample consists of 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.

In the following section we illustrate the procedure to compute our preferred measure of individual-level automation risk. Other measures are introduced as part of robustness checks in section 4.2.

3.2 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. (2016, 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 entail a risk of measurement errors, the fact that we use highly disaggregated occupation categories (4 digits) reduces assignment problems faced by previous studies.[13] Second, we regress Frey and Osborne's automation risk scores on a set of self-reported chacteristics reflecting the task content of inidviduals' job. These task variables are aimed at representing the engineering bottlenecks emerging from the experts' discussion, i.e. tasks that are difficult to automatize (Frey and Osborne, 2017).

Estimated coefficients capture the effect of job-related attributes on the automation risk of individuals' occupation. Similar to Arntz et al. (2016), 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 occupational level, our approach captures the variation in non-automatable tasks within occupations.

Descriptive statistics for the 10 task-related variables representing the engineering bottlenecks identified by Frey and Osborne (2017) are reported in Table 2. Figure A.2.1 in Appendix reports mean differences in task-related attributes by ER presence, sug-

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

gesting ER is indeed associated with richer (i.e. less monotone and more engaging) job designs. 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", "teamwork") 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 "monotone tasks" and "working at high speed".[14]

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 analyze the plausibility of the argument, 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 statistical association between the incidence of ER structures and job automation risk. Higher incidence of ER is associated with lower automation risk. In Figure 5, we 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.

4 Results

4.1 Baseline analysis

As the second step of our empirical strategy we study the association between endogenous automation risk and ER in a systematic regression analysis. We exploit the individual-level dimension of the EWCS data and consider the following baseline regression model:

$$\mathrm{AR}_i = \beta_0 + \beta_1 \, \mathrm{ER}_i + \mathbf{b}\mathbf{X}_i + \varepsilon_i \qquad (11)$$

where AR_i is an individual-level measure of automation risk; ER_i is a dummy variable which equals 1 when an employee representation 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 a large vector of occupational ISCO dummies); ε_i are the residuals.

[14] In Appendix, we compare the average automation score and the fraction of individuals at high risk of automation (>0.7) obtained in our sample with estimates reported by Arntz et al. (2016) using PIAAC. The distributions are broadly comparable.

In our first estimation round, we use the automation risk variable built as in Arntz et al. (2017). 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 salaried 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. In column 4, we add country, industry and year effects. Estimates reported in column 5 control for industry and country-specific time trends. Finally, in column 6, we report the results from a demanding specification in which we soak up all the variability across broadly defined occupations. The estimated parameter of ER remains negative and statistically significant across all the model specifications, consistently with our theoretical argument.

To better disentangle the interactions between ER and individual characteristics of the workers with respect to the risk of automation, we re-run our equation (11) by using a high risk of automation dummy as the dependent variable. Formally, 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.[15] We then estimate equation (11) by using a logit model and calculate the conditional correlations between ER and job automation risk by educational level. The results from the logit estimation are reported in Table 4, where the controls are again added progressively, while the estimations of the conditional correlations are obtained from the full model specification presented in column 6 of Table 4 and are reported graphically in Figure 7.

The logit estimates are broadly 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 2.8 percentage points in the probability of being exposed to high risk of automation (Column 3 of Table 4). Marginal effects obtained from the full model specification reported in Column 6 reveal that the presence of ER is associated with a reduction of 0.7 percentage point in the probability of being exposed to high risk of automation. As for the conditional effects, we find that the magnitude of the (negative) correlation between ER and the high automation risk

[15] Frey and Osborne (2017), Arntz et al. (2017) and Nedelkoska and Quintini (2018) classify automation risk as high when the probability of automation is above 0.7.

dummy is consistently higher for less educated employees. ER structures seem to help to insulate less-educated workers from the risk of automation by reshaping their task environment. For example, ER may compensate lower formal education credentials by fostering intensive investments in job training and firm-specific skills (Belloc et al., 2020).

4.2 Industry-level analysis

To test the robustness of our estimates to country and industry unobservables and to observable time-varying industry dimensions, we perform a fixed effects (FE) panel analysis on data averaged over country-industry-year cells over the period 2010-2015. For obtaining averaged variables, individual population weights are used. In particular, we use a country-industry-year automation risk averaged version of our individual-level automation risk variable. Doing so, we are able both to perform a panel FE regression where country-industry and time FE are eliminated and to account for additional cross-industry variability in dimensions not controlled for in our individual-level regressions. First, it has been argued that differences in job automation risk may reflect heterogeneous adoption of new technologies across sectors and countries. Low automation risk may result from past investments, which may have already contributed to replace labor by capital in performing automatable tasks. Hence, automation risk may reflect unused potential for automation (Arntz et al., 2016). To account for this factor, we control for capital intensity and utilization of information and communication technologies in our industry-country level regressions. Second, differences in automation risk may reflect differences in the extent to which firms outsource routine and automatable tasks. This may confound with the presence of employee representation structures if higher labor costs resulting from greater employees bargaining power create incentives for firms to contract out certain business activities to an external organization.[16]

Formally, we consider the following regression model:

$$\mathrm{AR}_{c,s,t} = \delta_0 + \delta_1\ \mathrm{ER}_{c,s,t} + \mathbf{d}\mathbf{W}_{c,s,t} + \text{Country-Sector FE} + \text{Time FE} + \epsilon_{c,s,t} \tag{12}$$

where c is the country, s the (one-digit) sector and t the year, and with $\epsilon_{c,s,t}$ being the residuals. The vector $\mathbf{W}_{c,s,t}$ includes the share of education, gender, age, occupation and firm size classes (averaged within country-sector-year cells) and time-varying industry controls. $\mathrm{AR}_{c,s,t}$ and $\mathrm{ER}_{c,s,t}$ have the same definition as in equation (11), but only vary across country-sector-year cells.

The results are presented in Table 5, where we add progressively employee-level and firm-level controls averaged for each country-industry-year cell and a set of time varying industry controls, including: value added to gross output ratio, net capital cost for ICT

[16] We include controls for value added/output ratio at the industry level as a proxy of outsourcing (Rakesh and Pulak, 2019).

to total labor cost ratio, net taxes on production to gross output ratio, and gross capital stock to total employees ratio. All the monetary variables are expressed in real terms. Finally, we add occupation effects, by means of a set of occupation-level variables, each measuring employment shares in a given occupation at 1 digit. Reassuringly, we find again a negative association between ER and automatability.

4.3 Robustness checks

As mentioned above, various ways of assessing automation risk have been proposed in the literature. In our baseline analysis, we exploit a measure that allows for differences in task content across workplaces within occupations. Nevertheless, most of the former studies assume homogeneous task content within occupations. Prominent examples include Costinot et al. (2011) and Frey and Osborne (2017). For comparison, we additionally estimate model (11), using these alternative measures of automation risk on the left-hand-side of the equation.

First, we test whether our results remain qualitatively unchanged when automation risk is measured in terms of job routineness, as in Costinot et al. (2011). Formally, we measure job routineness μ_i at a worker-level as $\mu_i = 1 - P_i$, where $P_i \in [0, 1]$ is a dummy variable which equals 1 when the job involves solving unforeseen problems' on the worker i's own and 0 otherwise. Notice that, while the original measure of Costinot et al. (2011) is computed at a six-digit occupation-level as provided in O*NET US data, our measure is obtained from the EWCS data and is at the individual-level. In this way, we are also able to include a large set of ISCO occupation dummies to control for occupation unobservables.

Second, we construct an alternative measure of automation risk by crosswalking the original occupation-level calculations of Frey and Osborne (2017) on the EWCS data. We mechanically import the occupation-specific automation risks as obtained by Frey and Osborne (2017) for 702 O*NET occupations to our 4-digit ISCO codes. In our exercise, these occupation-level automation risks are applied to all workers in each occupation for both 2010 and 2015.

Both when using the job routineness measure à la Costinot et al. (2011) and the original automation probabilities of Frey and Osborne (2017), the analysis of the correlation with ER is run at the individual-level over the pooled sample. The results are presented in Table 6 and Table 7, respectively. While in Table 6 we can exactly replicate the same specifications presented in Table 3, because the job routineness index μ_i varies at a worker-level, in Table 7 only five columns are displayed, because the automation probabilities of Frey and Osborne (2017) vary only across occupations and therefore occupation dummies cannot be added to the set of regressors. We follow the two approaches –i.e. one with within-occupation variation and one with only cross-occupation variation– to check the robustness of our estimates to the inclusion/exclusion of the occupation dimension.

Evidently, both approaches suggest that ER and automation risk are negatively correlated. This further supports our theoretical intuition and mitigates the possible concern that our baseline results are driven by the choice of the automation risk measure.

5 Historical examples

The empirical analysis confirms the existence of a negative relationship between job automation risk and the presence of ER bodies at the workplace level. Unfortunately, available data do not allow us to carry out a direct test of the mechanisms underlying such relationship. However, additional insights can be obtained by looking at the historical experience and policy developments in Nordic countries, such as Sweden and Norway, during the 1960s and 1970s. Interestingly, these countries now exhibit relatively low job automation risk, high union coverage and widespread workplace ER in comparison to other countries.[17] Historical evidence and case studies suggest that the kind of mutual reinforcing dynamics between job design and workplace organization highlighted in our theoretical framework can help to rationalize the trajectory of these countries.

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 analyzed experiences of formal arrangements granting ER at the board level. The second phase investigated the condition for fostering personal participation at the shop-floor 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 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

[17] In Appendix Figure A.2.2, we plot the kernel density of automation risk grouping countries according to the classification of industrial relations regimes proposed by Visser (2009). The estimated distribution of automation risk for Nordic countries ("North") lies more to the left than the distribution for other groups indicating lower average automation risk for these countries.

rights over financial and organizational 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, organizational changes and labor 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, the combination of these different policy experiments and legal initiatives favored the emergence of production conventions characterized by rich job designs and extensive ER in many Norwegian industries. Such conventions, which persisted over time, helped containing the excessive recourse to job routinization as tool for labor 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 organizational levels (Martin, 1987). It became evident that organizational 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 organization, 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.

In sum, similarly to the Norwegian case, Sweden's work arrangements followed 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 organization, 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).[18] Altogether, the reinforcing dynamics between job design and workplace governance favoured the emergence 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.

6 Discussion and Conclusion

Most researchers agree that nearly all jobs will be affected by automation in the next decades. Less is known, however, about the determinants of automation and the reasons why exposure to job automation risk largely varies across firms and sectors. In particular, unexplored is how institutions of labor organization affect the pace and direction of the automation processes, by influencing the task content within occupations.

In this paper, we tackled this issue by focusing on the role of workplace ER bodies, which were found to shape the labor relationship in many important respects (Freeman and Medoff, 1984). We argued that ER relates to job automation risk via a two-way-causality: on the one hand, higher automation risk makes ER less likely to be established, because workers do not expect to gain much by organizing labor; on the other, ER reduces automation risks, as it favours group effort commitments thereby reducing the need for employers to convert complex tasks into routine and easier to monitor assignments. On

[18] 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 labor market tightness, limited availability of foreign workers and strong competitive pressures on low productivity firms resulting from solidaristic wage policies (Barth et al., 2014).

this basis, we predicted the existence of a negative relationship between ER and job automation risk. We tested this prediction on EWCS data by relying on a worker-level measure of automation risk based on a set of task content characteristics (as in Arntz et al., 2017). The results of the empirical analysis provide support for our hypothesis.

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 do not provide direct evidence on the underlying mechanism suggested by our model, i.e. the use of job design as a discipline device vs. high-performance norm and skill upgrading sustained by the presence of ER. However, additional evidence derived from the experience of Nordic countries, in particular Norway and Sweden, suggests that the channels highlighted in our organizing evolutionary framework are historically plausible. Second, the cross-sectional structure of the data makes 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. Third, in our framework the possibility of effort extraction via institutionalized commitment requires a fairly balanced engagement by the parties involved in bargaining disputes, which is not always present in real world interactions. In particular, one may wonder whether the existence of an industrial relation system characterized by a strong cooperative culture and trust is actually a precondition for the role that we assign to ER in our model. However, historical evidence reveals that the extent to which workplace cooperation is a prerequisite or the outcome of granting workers control rights is unclear. For instance, Norway and Sweden experienced the highest levels of industrial conflict in the world in the 1920s and early 1930s, way before developing their social democratic policies and labor institutions (Moene and Wallerstein, 2006).

The results of the paper contributes to contemporary policy discussions in relation to the governance of AI and the automation process (Goldfarb et al., 2019; Savona, 2019; Goos, 2018). The growing awareness about the benefits and costs of automation has indeed spurred many academic and public policy debates. The latter are usually concerned with two main objectives: a) to promote investments in automation-related technologies that ensure sufficiently large productivity gains; b) to design labor market institutions and social insurance policies that favour the smooth reallocation of displaced workers towards non-automated tasks. On this respect, our study adds that a relevant role in the governance of AI debate is to be played by the institutions that help labor organization at the workplace level.

In particular, this paper shows that despite the great potential of AI-related technologies, in certain settings the automation process can lead to sub-optimal results. This is due not only to the possibility that firms invest in "wrong" technologies, i.e. those that ensure insufficient productivity improvements (Acemoglu and Restrepo, 2020b), but also to the fact that when confronted with disorganized labor, 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 and information asymmetries, the exposition of workers to high automation risk can serve as a labor discipline device that enables greater effort extraction. In these cases, the introduction of ER bodies represents a decentralized labor institution that helps re-balancing authority relations within firms, allowing workers and capital owners to coordinate on a socially superior organizational equilibrium. In this type of job environment, shared control rights and rich job designs enable effort extraction via institutionalized commitment rather than discipline, ensuring that both parties are better off.

Three important clarifications are necessary though. The first one concerns insights for the design of interventions. In our theoretical framework workplace governance and job design fit together complementarily, leading to the existence of multiple organizational equilibria. This implies that to shift from one equilibrium to the other simultaneous changes along multiple organizational domains are needed. On this respect, the historical experiences of Nordic countries is revealing. 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. When applied to the case of automation, these historical experiences suggest that interventions governing the automation process need to be forcefully multi-dimensional. 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.

The second point that need to be clarified is that the efficacy of ER and job design-related interventions depends on the characteristics of the surrounding social and economic environment. In particular, the comparative analysis carried out on the basins of attraction of the two organizational equilibria reveals that three factors are of particular relevance: the cost of automation technologies, the easiness of collective organization and the cost of job termination. While the former is driven primarily by scientific and technical advances, the latter depend on the combination of different 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.[19] Similarly, a rising level of unemployment due to unfavorable trends of the economic cycle

[19]The cost of collective action is not only driven by features of the regulatory environment. Formal institutions may coevolve with other ideological and cultural factors affecting the workers' willingness to establish ER structures and engage in cooperative labor-management relationships.

tend to increase the costs of job termination. As a consequence labor discipline becomes more effective than institutionalized commitment as a tool to extract work effort. Everything else equal, this makes a transition to the equilibrium with shared control rights and rich job design less likely to occur.

Finally, it is important to clarify that our results should not be interpreted as suggesting that ER operates as a force against technological advancements. The fact that the strengthening of ER-related institutions favours the adoption of less automation-prone job designs does not imply that no production task is ever automatized. Once again the experience of the Nordic countries is inspiring. Despite of a relatively low job automation risk, some of these countries register a comparatively high number of per-worker industrial robots (IFR, 2019). Even more interesting is the fact that early versions of the latter were introduced exactly during the period of intensive policy experiments aimed at improving work arrangements (Deutsch, 1986). Yet, in these countries the presence of strong labor organization implied that the share of automatable tasks was determined more by technical opportunities, than by labor discipline, targeting in particular the substitution of unhealthy and unpleasant jobs (Aguren and Edgren, 1980). As a consequence the co-existence of widespread ER institutions and rich job designs favored the selection of efficiency-enhancing technologies, which at the same time improved working conditions.

In general terms we believe that the main message of our study is that the impact of automation should be evaluated along multiple dimensions. Alongside the obvious and well-investigated technological dimension, the diffusion and impact of automation depend on a set of social and political factors, among which firm-level institutional bodies enabling democratic participation in the production process play an important role. By restraining incentives towards the adoption of excessive automation-prone job design, they can help making automation welfare-improving. Policy debates should avoid technological determinism and devoid greater attention to the complex dynamics through which the interaction of technological and socio-institutional forces shape the future of work.

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Figures and Tables

Table 1: Payoff matrix.

	Worker (w)	
Owner (o)	With ER (G_H)	Without ER (G_L)
High automability (D_H)	$q\theta - s - k,\ s - \theta + \theta^2/2 - c$	$q\theta - s - k,\ s - \theta + \theta^2/2$
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:				
Working at high speed (from never to always)	3.535	1	7	2.025
Visiting customers or clients (1=yes, 0=no)	0.276	0	1	0.447
Solving unforeseen problems autonomously (1=yes, 0=no)	0.812	0	1	0.390
Monotonous tasks (1=yes, 0=no)	0.466	0	1	0.498
Complex tasks (1=yes, 0=no)	0.573	0	1	0.494
Learning new things (1=yes, 0=no)	0.682	0	1	0.465
Applying own ideas (from never to always)	3.599	1	5	1.333
Influencing important decisions (from never to always)	3.226	1	5	1.372
Measures of automation risk				
Risk of automation (Arntz et al., 2017)	0.534	0.240	0.876	0.130
High risk of automation (Risk > 0.7)	0.121	0	1	0.326
Job routineness (Costinot et al., 2011)	0.199	0	1	0.399
FO's probability of automation (Frey and Osborne, 2017)	0.570	0.003	0.990	0.373
Employee representation				
ER	0.472	0	1	0.499
Control variables				
Female	0.515	0	1	0.499
Age	41.633	15	91	12.012
Education: primary	0.057	0	1	0.232
Education lower secondary	0.145	0	1	0.352
Education: upper secondary	0.404	0	1	0.490
Education: post-secondary	0.056	0	1	0.230
Education: tertiary	0.302	0	1	0.459
Firm size (1-9)	0.391	0	1	0.488
Firm size (10-249)	0.390	0	1	0.487
Firm size (250+)	0.172	0	1	0.377

Notes: Descriptive statistics are obtained over the EWCS data, 2010 and 2015 waves. Sample restricted to salaried workers.

Table 3: Pooled OLS results based on Arntz et al. (2017).

	[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	-0.028***	-0.012***	-0.018***	-0.004***	-0.005***	-0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Female		0.009***	0.010***	0.025***	0.025***	0.020***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age		-0.001***	-0.001***	-0.002***	-0.002***	-0.002***
		(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.		-0.035***	-0.037***	-0.016***	-0.017***	-0.006***
		(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Upper-secondary edu.		-0.066***	-0.068***	-0.055***	-0.055***	-0.024***
		(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Post-secondary edu.		-0.092***	-0.095***	-0.077***	-0.077***	-0.032***
		(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Tertiary edu.		-0.144***	-0.147***	-0.118***	-0.118***	-0.044***
		(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Estimation	OLS	OLS	OLS	OLS	OLS	OLS
No. Obs.	62792	60503	58551	57941	57941	57870
R^2	0.012	0.129	0.132	0.238	0.244	0.366
Individual-level controls	NO	YES	YES	YES	YES	YES
Firm-level controls	NO	NO	YES	YES	YES	YES
Country dummies	NO	NO	NO	YES	YES	YES
Year dummies	NO	NO	NO	YES	YES	YES
Industry dummies	NO	NO	NO	YES	YES	YES
Country×Year dummies	NO	NO	NO	NO	YES	YES
Industry×Year dummies	NO	NO	NO	NO	YES	YES
Occupation dummies	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. Standard errors in parentheses are heteroschedasticity robust. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Pooled logit results based on Arntz et al. (2017).

	[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	-0.038***	-0.012***	-0.028***	-0.007**	-0.010***	-0.008**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Female		0.011***	0.014***	0.040***	0.039***	0.039***
		(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Age		0.001	0.000	-0.002***	-0.002***	-0.002***
		(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.		-0.070***	-0.081***	-0.035***	-0.036***	-0.008
		(0.010)	(0.010)	(0.010)	(0.010)	(0.007)
Upper-secondary edu.		-0.139***	-0.150***	-0.125***	-0.122***	-0.038***
		(0.009)	(0.009)	(0.009)	(0.009)	(0.007)
Post-secondary edu.		-0.191***	-0.205***	-0.162***	-0.159***	-0.049***
		(0.010)	(0.011)	(0.010)	(0.010)	(0.009)
Tertiary edu.		-0.263***	-0.275***	-0.224***	-0.221***	-0.074***
		(0.009)	(0.009)	(0.009)	(0.009)	(0.007)
Estimation	Logit	Logit	Logit	Logit	Logit	Logit
No. Obs.	62792	60503	58551	57941	57941	57870
Individual-level controls	NO	YES	YES	YES	YES	YES
Firm-level controls	NO	NO	YES	YES	YES	YES
Country dummies	NO	NO	NO	YES	YES	YES
Year dummies	NO	NO	NO	YES	YES	YES
Industry dummies	NO	NO	NO	YES	YES	YES
Country×Year dummies	NO	NO	NO	NO	YES	YES
Industry×Year dummies	NO	NO	NO	NO	YES	YES
Occupation dummies	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. Marginal effects are displayed. Standard errors in parentheses are heteroschedasticity robust. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Country-industry panel FE results based on Arntz et al. (2017).

	[1] Average risk of automation	[2] Average risk of automation	[3] Average risk of automation	[4] Average risk of automation
ER	-0.023***	-0.077***	-0.056***	-0.070***
	(0.013)	(0.026)	(0.024)	(0.025)
Female			0.045	0.059
			(0.042)	(0.045)
Age			-0.031**	-0.034**
			(0.015)	(0.014)
Age^2			0.000*	0.000**
			(0.000)	(0.000)
Lower-secondary edu.			0.008	0.122**
			(0.043)	(0.055)
Upper-secondary edu.			-0.072	0.078
			(0.046)	(0.064)
Post-secondary edu.			-0.063	0.094
			(0.076)	(0.083)
Tertiary			-0.122*	0.105
			(0.071)	(0.080)
Estimation	Panel FE	Panel FE	Panel FE	Panel FE
No. Obs.	840	190	190	190
R^2	0.009	0.175	0.434	0.591
Industry-country FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Industry controls	NO	YES	YES	YES
Employee-average controls	NO	NO	YES	YES
Firm-average controls	NO	NO	YES	YES
Occupation shares	NO	NO	NO	YES

Notes: Estimation by panel FE estimation on a panel sample of country-industry observations for 2010 and 2015. Risk of automation is computed as in Arntz et al. (2017) on EWCS data. Automation risk and the independent variables are averaged over country-industry-year cells, by using individual population weights. Industry controls include: value added to gross output ratio, net capital cost for ICT to total labor cost ratio, net taxes on production to gross output ratio, gross capital stock to total employees ratio. Firm-average controls include average firm size. Occupation shares is a set of occupation variables measuring employment shares in each occupation. Primary education is the benchmark category for the educational classes. Standard errors in parentheses are heteroschedasticity robust. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Pooled logit results based on Costinot et al. (2011).

	[1] Job routineness	[2] Job routineness	[3] Job routineness	[4] Job routineness	[5] Job routineness	[6] Job routineness
ER	-0.069***	-0.045***	-0.034***	-0.024***	-0.027***	-0.023***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Female		0.043***	0.042***	0.052***	0.052***	0.039***
		(0.003)	(0.003)	(0.008)	(0.003)	(0.004)
Age		-0.008***	-0.007***	-0.008***	-0.009***	-0.008***
		(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.		-0.046***	-0.044***	-0.037***	-0.037***	-0.016*
		(0.009)	(0.010)	(0.010)	(0.010)	(0.009)
Upper-secondary edu.		-0.082***	-0.079***	-0.111***	-0.110***	-0.050***
		(0.009)	(0.009)	(0.010)	(0.010)	(0.008)
Post-secondary edu.		-0.130***	-0.129***	-0.144***	-0.142***	-0.062***
		(0.010)	(0.010)	(0.011)	(0.011)	(0.010)
Tertiary edu.		-0.187***	-0.181***	-0.196***	-0.195***	-0.079***
		(0.009)	(0.009)	(0.010)	(0.010)	(0.009)
Estimation	Logit	Logit	Logit	Logit	Logit	Logit
No. Obs.	66439	64016	61789	61134	61134	60719
Individual-level controls	NO	YES	YES	YES	YES	YES
Firm-level controls	NO	NO	YES	YES	YES	YES
Country dummies	NO	NO	NO	YES	YES	YES
Year dummies	NO	NO	NO	YES	YES	YES
Industry dummies	NO	NO	NO	YES	YES	YES
Country×Year dummies	NO	NO	NO	NO	YES	YES
Industry×Year dummies	NO	NO	NO	NO	YES	YES
Occupation dummies	NO	NO	NO	NO	NO	YES

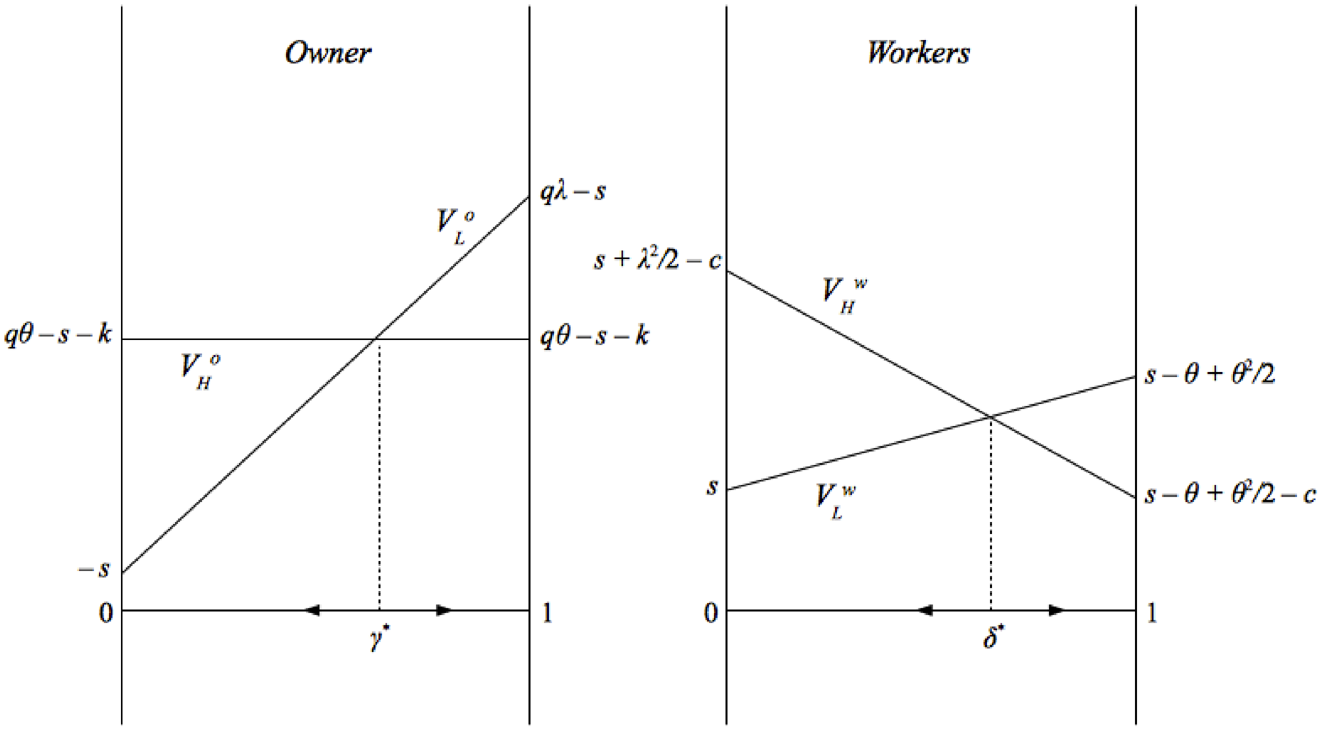
Notes: Estimation by logit on a pooled sample of individual-level observations. Risk of automation is computed by means of task routineness as in Costinot et al. (2011) on EWCS data. Firm-level controls include firm size. Primary education is the benchmark category for the educational classes. Marginal effects are displayed. Standard errors in parentheses are heteroschedasticity robust. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Pooled OLS results based on Frey and Osborne (2017).

	[1] FO's probability of automation	[2] FO's probability of automation	[3] FO's probability of automation	[4] FO's probability of automation	[5] FO's probability of automation
ER	-0.105***	-0.067***	-0.065***	-0.025***	-0.026***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Female		0.019***	0.020***	0.075***	0.075***
		(0.003)	(0.003)	(0.003)	(0.003)
Age		-0.006***	-0.006***	-0.006***	-0.006***
		(0.001)	(0.001)	(0.001)	(0.000)
Age^2		0.000***	0.000***	0.000***	0.000***
		(0.000)	(0.000)	(0.000)	(0.000)
Lower-secondary edu.		-0.009	-0.006	0.008	0.008
		(0.007)	(0.007)	(0.007)	(0.007)
Upper-secondary edu.		-0.019***	-0.016***	-0.016**	-0.017**
		(0.006)	(0.006)	(0.007)	(0.007)
Post-secondary edu.		-0.074***	-0.073***	-0.056***	-0.057***
		(0.008)	(0.008)	(0.009)	(0.009)
Tertiary edu.		-0.283***	-0.279***	-0.223***	-0.224***
		(0.006)	(0.007)	(0.007)	(0.007)
Estimation	OLS	OLS	OLS	OLS	OLS
No. Obs.	63533	61177	59077	58467	58467
R^2	0.019	0.127	0.131	0.236	0.238
Individual-level controls	NO	YES	YES	YES	YES
Firm-level controls	NO	NO	YES	YES	YES
Country dummies	NO	NO	NO	YES	YES
Year dummies	NO	NO	NO	YES	YES
Industry dummies	NO	NO	NO	YES	YES
Country×Year dummies	NO	NO	NO	NO	YES
Industry×Year dummies	NO	NO	NO	NO	YES

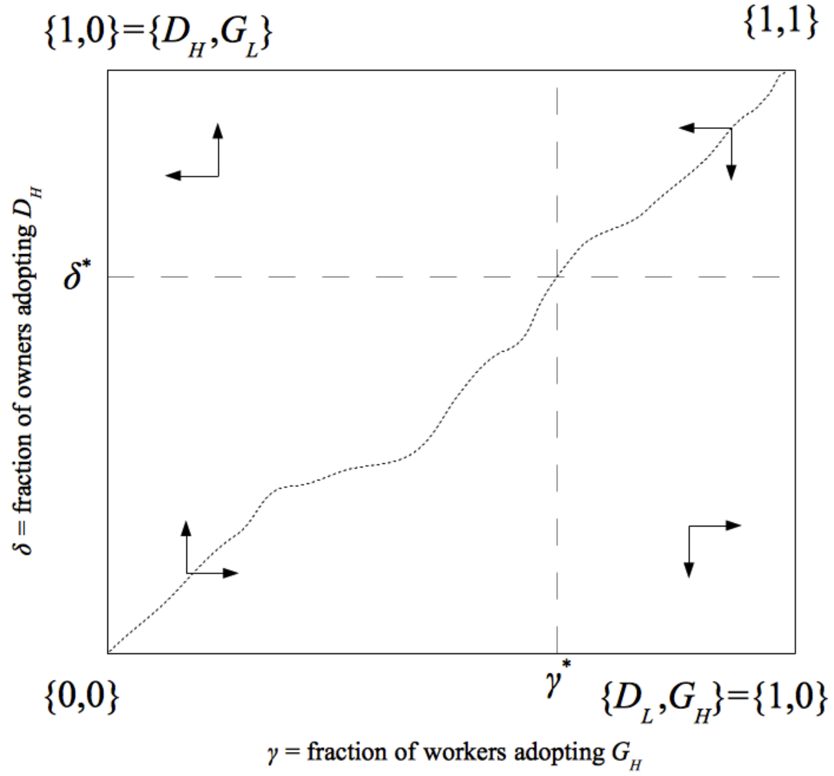
Notes: Estimation by OLS on a pooled sample of individual-level observations. Probability of automation is measured by mechanic extrapolation of automation probabilities calculated by Frey and Osborne (2017) to EWCS data, by matching ISCO codes. Firm-level controls include firm size. Primary education is the benchmark category for the educational classes. Standard errors in parentheses are heteroschedasticity robust. *** p<0.01, ** p<0.05, * p<0.1.

Figure 1: Expected payoffs to owner and workers.



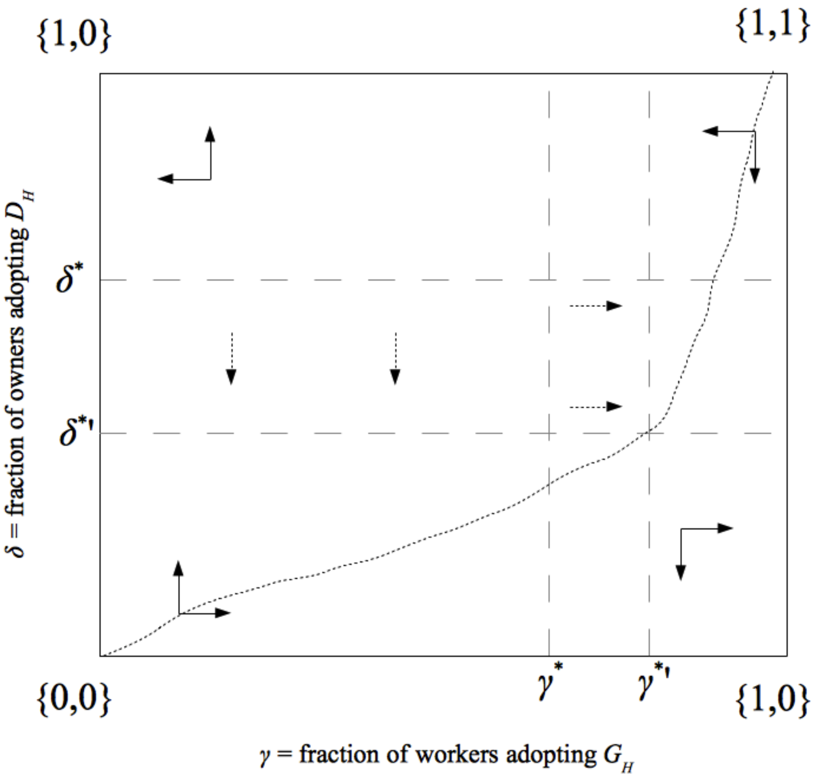
Notes: This figure displays the expected payoff functions; δ is the fraction of owners adopting D_H and γ is the fraction of workers adopting G_H. The vertical intercepts are from Table 1.

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



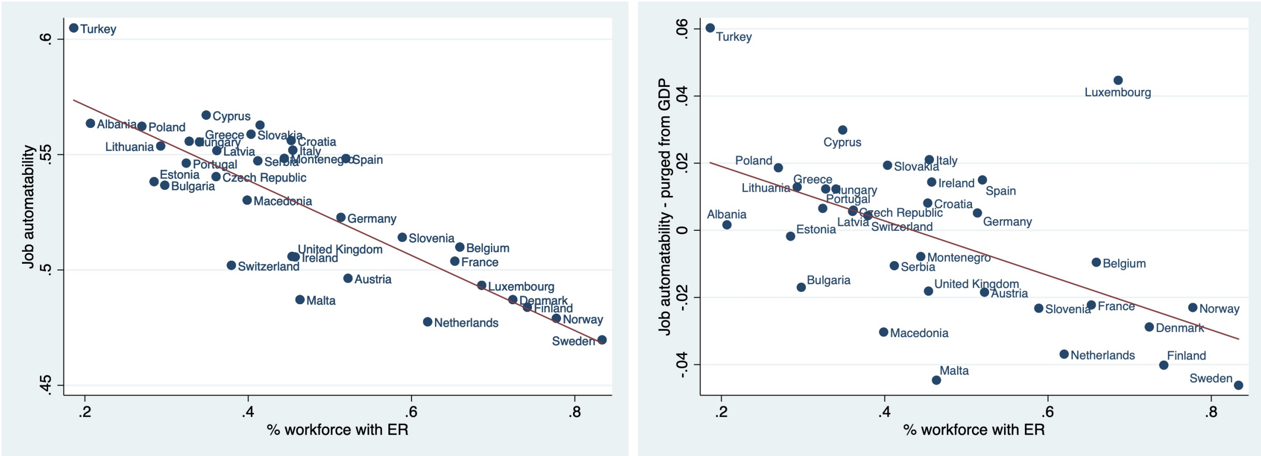
Notes: The arrows represent the disequilibrium adjustment in the number of owners (vertical movements) and workers (horizontal movements).

Figure 3: Changes in the basin of attraction.



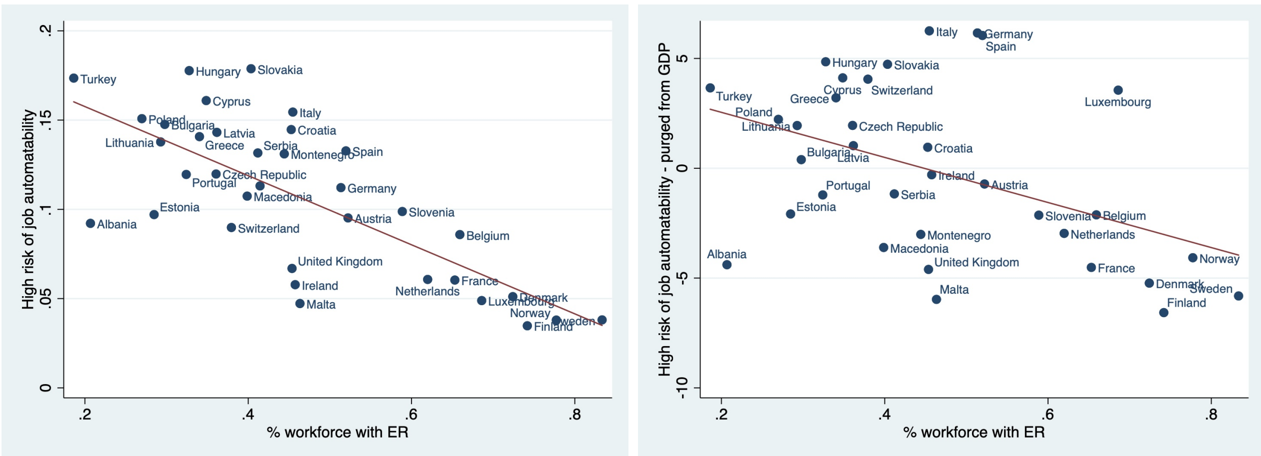
Notes: The figure shows the changes in the size of the basins of attraction when the cost of collective action c increases (δ^* reduces to $\delta^{*\prime}$) and the expected cost of automation k reduces (γ^* increases to $\gamma^{*\prime}$). Overall, these changes make the relatively inefficient convention $\{1, 0\}$ more likely to emerge.

Figure 4: ER and risk of automation: correlation of country averages over 2010 and 2015.



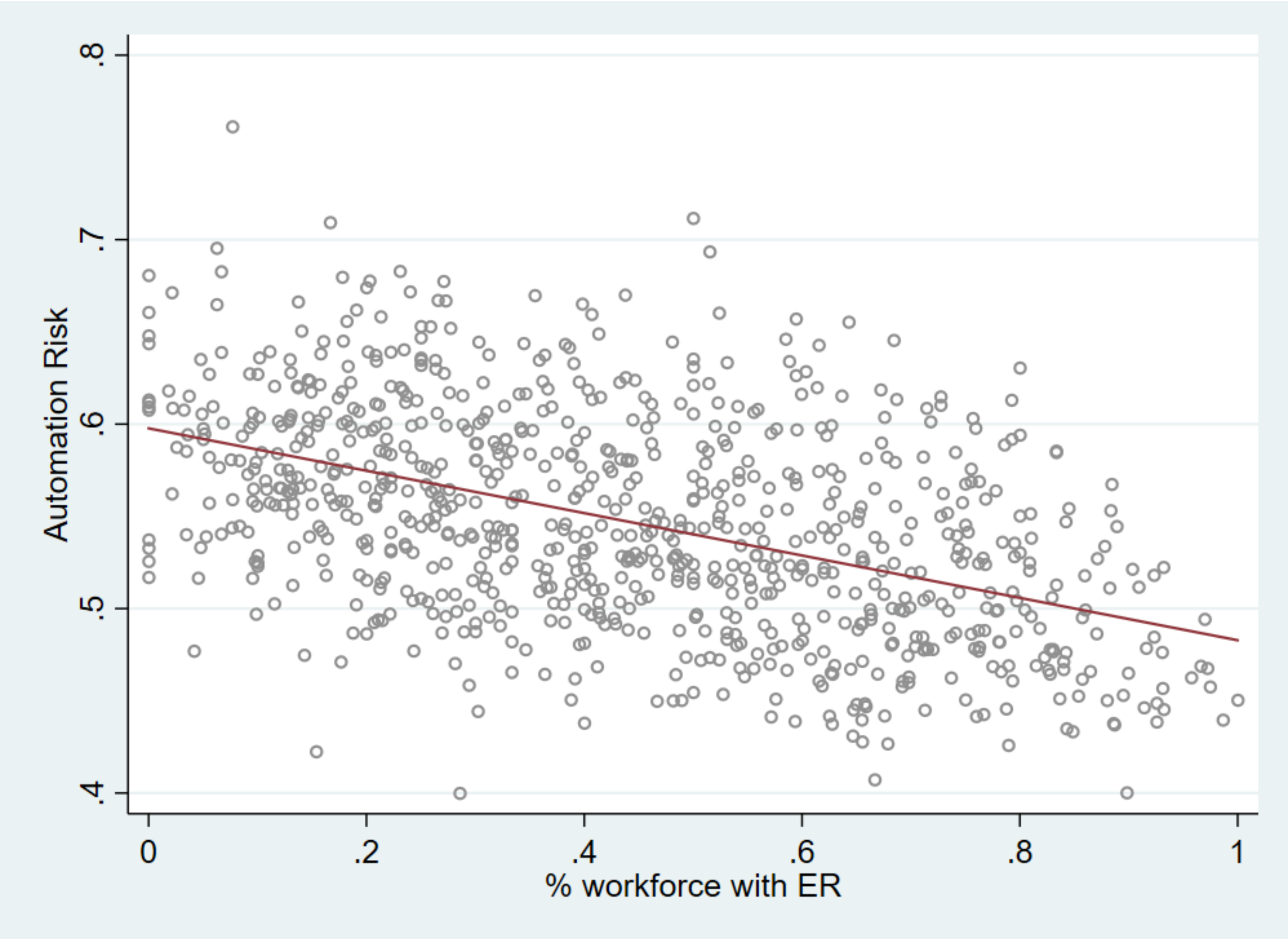
Notes: The figures display the correlation between the share of workforce employed in production units with ER and our baseline measure of job automatability (computed as in Arntz et al. (2017)), both averaged at a country level over 2010 and 2015 and based on EWCS data. In the right-hand side figure, we use job automatability values purged from countries' GDP: these values are obtained as residuals from regressing our baseline measure of job automatability ($\times$ 100) against countries' GDP/1000 in PPP (the regression coefficient of GDP is -0.122, with p-value=0.000).

Figure 5: ER and high risk of automation: correlation of country averages over 2010 and 2015.



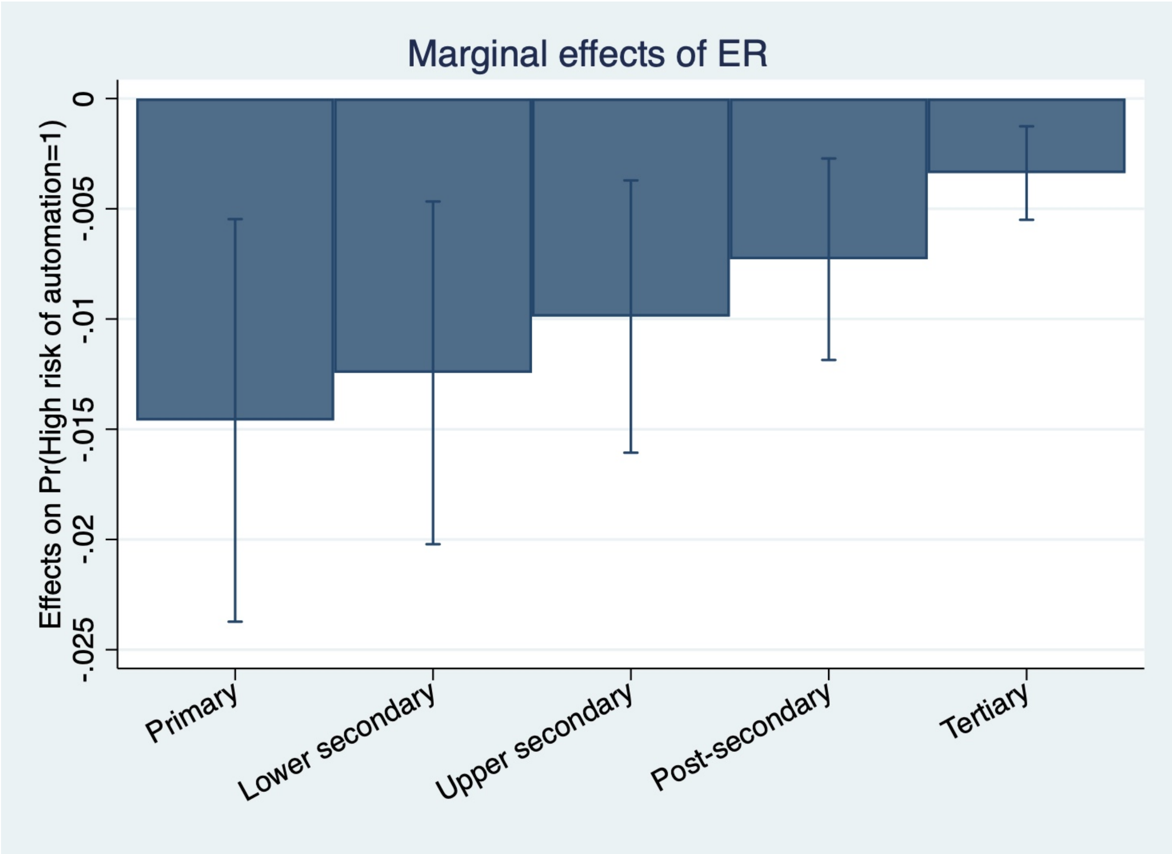
Notes: The figures display the correlation between the share of workforce employed in production units with ER and our measure of high risk of job automatability (computed as in Arntz et al. (2017)) coded as a dummy variable which equals 1 when the risk of automation is equal to or greater than 0.7, both averaged at a country level over 2010 and 2015 and based on EWCS data. In the right-hand side figure, we use job automatability values purged from countries' GDP: these values are obtained as residuals from regressing (by means of logit) our measure of high risk of job automatability against countries' GDP/1000 in PPP (the regression coefficient of GDP is -0.018, with p-value=0.000).

Figure 6: ER and risk of automation: correlation of industry-country-year averages.



Notes: This figure displays the correlation between the share of workforce employed in production units with ER and our baseline measure of job automatability (computed as in Arntz et al. (2017)), both averaged at a country-industry-year level and based on EWCS data.

Figure 7: Conditional correlations by educational level.



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 Eqs. (1), (2), we have:

$$u_w(D_H,G_H) = s - e_w^2/2 - (1-e_w)\theta - c \quad , \quad u_w(D_H,G_L) = s - e_w^2/2 - (1-e_w)\theta \quad \text{(A.1.13)}$$

$$u_w(D_L,G_H) = s + \lambda e_W - e_w^2/2 - c \quad , \quad u_w(D_L,G_L) = s - e_w^2/2 \quad \text{(A.1.14)}$$

$$u_o(D_H,G_H) = u_o(D_H,G_L) = qe_w - s - k \quad , \quad u_o(D_L,G_H) = u_o(D_L,G_L) = qe_w - s \quad \text{(A.1.15)}$$

Moreover, given Remark 1, we have:

$$e_w^*(D_H,G_H) = e_w^*(D_H,G_L) = \theta \quad , \quad e_w^*(D_L,G_H) = \lambda \quad , \quad e_w^*(D_H,G_L) = 0 \quad \text{(A.1.16)}$$

where $e_w^*(D,G)$ is w's optimal level of effort under arrangement $\{D,G\}$. By replacing effort levels from into Eqs. (A.1.4) into Eqs. (A.1.1), (A.1.2) and (A.1.3) we obtain the following results:

$$u_o(D_H,G_H) = u_o(D_H,G_L) = q\theta - s - k \;\; , \;\; u_o(D_L,G_H) = q\lambda - s \;\; , \;\; u_o(D_L,G_L) = -s \quad \text{(A.1.17)}$$

$$u_w(D_H,G_H) = s - \theta + \theta^2/2 - c \quad , \quad u_w(D_H,G_L) = s - \theta + \theta^2/2 \quad \text{(A.1.18)}$$

$$u_w(D_L,G_H) = s + \lambda^2/2 - c \quad , \quad u_w(D_L,G_L) = s \quad \text{(A.1.19)}$$

A.1.2 Proof of Proposition 1

$\{D_L, G_L\}$ is proven to be Nash equilibrium as long as: (a) $-s > q\theta - s - k$, and (b) $s > s + \lambda^2/2 - c$. Condition (a) and (b) reduce to $k > q\theta = \bar{k}$ and $c > \lambda^2/2 = \bar{c}$, respectively. Similarly, $\{D_H, G_L\}$ is a Nash equilibrium as long as: (c) $q\theta - s - k > -s$ and (d) $s - \theta + \theta^2/2 > s - \theta + \theta^2/2 - c$. Condition (c) reduces to $k < q\theta = \bar{k}$, while condition (d) is self-explained. Finally, $\{D_L, G_H\}$ is a Nash equilibrium as long as: (e) $q\lambda - s > q\theta - s - k$ and (f) $s + \lambda^2/2 - c > s$. Condition (e) and (f) reduce to $k > q(\theta - \lambda)$ and $c < \lambda^2/2 = \bar{c}$. It follows that if $\lambda > \theta$, then condition (e) is always satisfied. Moreover: *(i)* when $k > \bar{k}$ and $c > \bar{c}$ conditions (a) and (b) are satisfied but not conditions (c) and (f), hence $\{D_L, G_L\}$ in the only Nash equilibrium; *(ii)* when $k < \bar{k}$ and $c > \bar{c}$ conditions (c) and (b) are satisfied but not conditions (a) and (f), hence $\{D_H, G_L\}$ in the only Nash equilibrium; *(iii)* when $k > \bar{k}$ and $c < \bar{c}$ conditions (a) and (f) are satisfied but not conditions (b) and (c), hence $\{D_L, G_H\}$ in the only Nash equilibrium; *(iv)* when $k < \bar{k}$ and $c < \bar{c}$ conditions (c) and (f) are satisfied but not conditions (a) and (b), hence $\{D_H, G_L\}$ and $\{D_L, G_H\}$ are both Nash equilibria.

A.1.3 Proof of Proposition 2

For any $\lambda > \theta$, $q\lambda - s > q\theta - s - k$ which implies that o is always better off under arrangement $\{D_L, G_H\}$ than under arrangement $\{D_H, G_L\}$. It follows that a necessary and sufficient condition for $\{D_L, G_H\}$ to Pareto dominates $\{D_H, G_L\}$ is that $s + \lambda^2/2 - c > s - \theta + \theta^2/2$, which reduces to $c < \lambda^2/2 + \theta - \theta^2/2 = \bar{c} + \theta - \theta^2/2$. This, together with the results of Proposition 1, implies that when both $\{D_H, G_L\}$ and $\{D_L, G_H\}$ are Nash equilibria and and $\theta < 2$, the former Pareto dominates the latter.

A.1.4 Proof of Proposition 3

The five cultural-technological equilibria are derived by simply 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 analyzing the Jacobean Matrix $J(\delta, \gamma)$ associated to system (7)-(8), which takes the following form:

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

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

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

from which it follows that

$$Tr(J) = \alpha\beta\left(q\theta - k + \frac{\lambda^2}{2} - c\right) \quad , \quad Det(J) = \alpha^2\beta^2\,(q\theta - k)\left(\frac{\lambda^2}{2} - c\right) \tag{A.1.20}$$

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

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

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

from which it follows that

$$Tr(J) = -\alpha\beta(q\theta - k + c) \qquad , \qquad Det(J) = \alpha^2\beta^2 c(q\theta - k) \tag{A.1.21}$$

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

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

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

from which it follows that

$$Tr(J) = \alpha\beta\left[q(\theta - \lambda) - k - \frac{\lambda^2}{2} + c\right] \quad , \quad Det(J) = -\alpha^2\beta^2\left[q(\theta - \lambda) - k\right]\left(\frac{\lambda^2}{2} - c\right) \tag{A.1.22}$$

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

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

$$J = \begin{pmatrix} -\alpha\beta\left[q(\theta - \lambda) - k\right] & 0 \\ 0 & \alpha\beta c \end{pmatrix}$$

from which it follows that

$$Tr(J) = -\alpha\beta\left[q(\theta - \lambda) - k\right] + \alpha\beta c \qquad , \qquad Det(J) = -\alpha^2\beta^2 c\left[q(\theta - \lambda) - k\right] \tag{A.1.23}$$

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

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

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

from which it follows that

$$Det(J) = -\frac{\lambda^2 - 2c}{2}\left(1 - \frac{\lambda^2 - 2c}{2}\right)\alpha\beta(-q\lambda)\frac{q\theta - k}{q\lambda}\left(1 - \frac{q\theta - k}{q\lambda}\right)\alpha\beta\left(-\frac{\lambda^2}{2}\right) \tag{A.1.24}$$

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

A.2 Empirical Appendix

Table A.2.1: Automatability and self-reported task content.

Task content	(1)
Working at high speed	0.013***
	(0.001)
Dealing with people	-0.016***
	(0.001)
Visiting customers or clients	-0.083***
	(0.005)
Solving unforeseen problems	-0.022***
	(0.007)
Monotonous tasks	0.088***
	(0.005)
Complex tasks	-0.059***
	(0.006)
Learning new things	-0.037***
	(0.006)
Teamwork	-0.016***
	(0.005)
Applying own ideas	-0.034***
	(0.002)
Influencing important decisions	-0.013***
	(0.002)
Observations	37,891

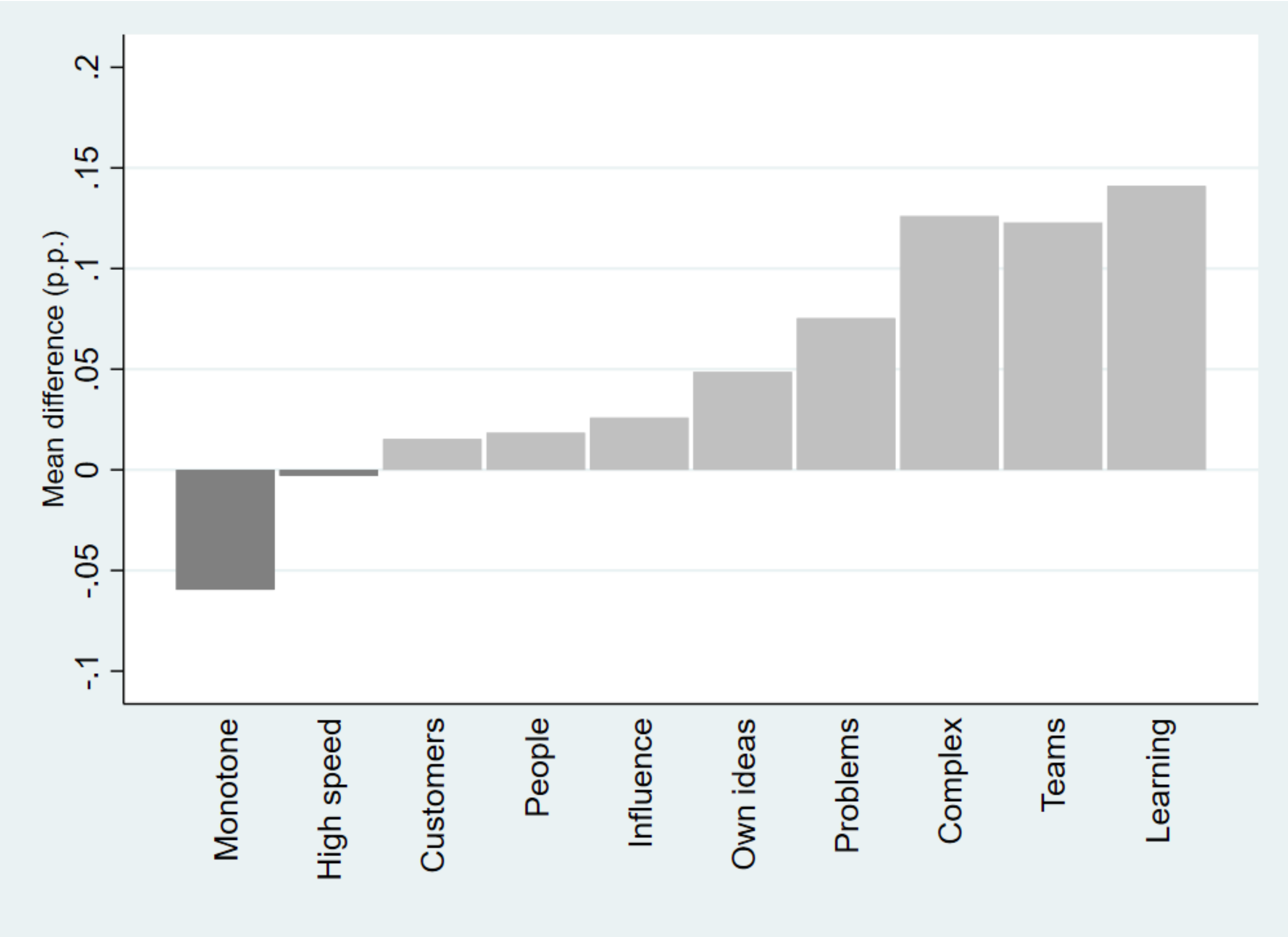
Notes: Based on individuals' self-reported task content in EWCS (2015). Marginal effects are displayed. Sample restricted to salaried workers. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.2.2: Measures of automation risk (AR): comparison with Arntz et al. (2016).

Country	[1] %High Risk Arntz et al. (2016)	[2] Mean AR Arntz et al. (2016)	[3] % High Risk EWCS2010	[4] Mean AR EWCS2010	[5] % High Risk EWCS2015	[6] Mean AR EWCS2015
Austria	12%	43%	11%	51%	10%	50%
Belgium	7%	38%	9%	52%	9%	51%
Czech Republic	10%	44%	15%	55%	12%	54%
Denmark	9%	38%	6%	48%	5%	49%
Estonia	6%	36%	14%	53%	10%	54%
Finland	7%	35%	5%	51%	3%	48%
France	9%	38%	14%	54%	6%	50%
Germany	12%	43%	13%	54%	11%	52%
Ireland	8%	36%	11%	51%	6%	51%
Italy	10%	43%	20%	58%	15%	55%
Netherlands	10%	40%	6%	50%	6%	48%
Norway	10%	37%	4%	49%	4%	48%
Poland	7%	40%	15%	54%	15%	56%
Slovakia	11%	44%	17%	57%	18%	56%
Spain	12%	38%	17%	55%	13%	55%
Sweden	7%	36%	5%	48%	4%	47%
UK	10%	39%	11%	52%	7%	51%

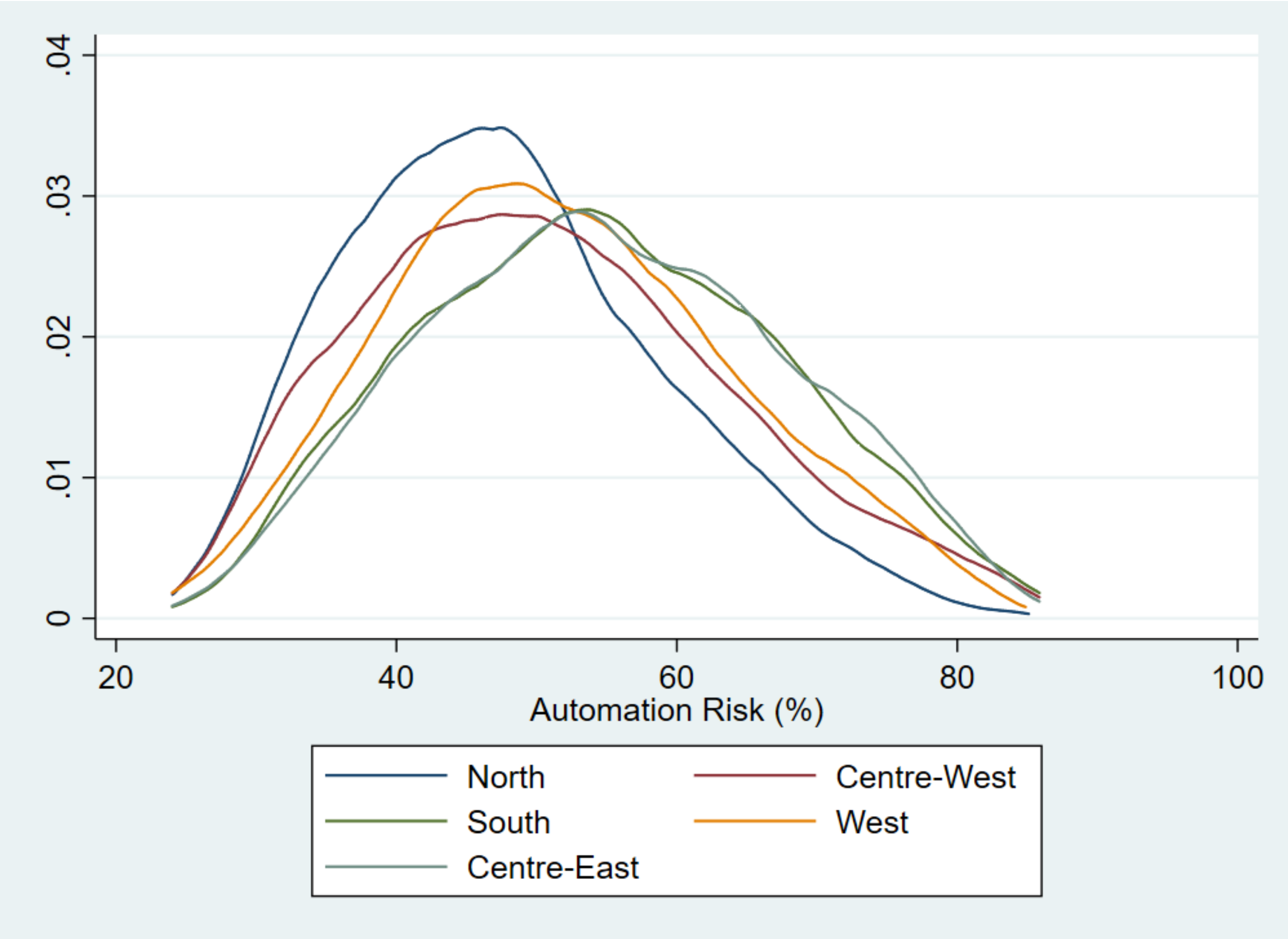
Notes: Columns 1-2 reproduce calculations reported in Arntz et al. (2016) for countries available in both PIAAC and EWCS. Columns 3-6 report our measures of automation risk constructed upon data from EWCS. Mean AR refers to the average risk of automation and % High Risk to the share of individuals at high risk of automation in each country (AR>0.7).

Figure A.2.1: Mean differences in task-related attributes by presence of ER (p.p.).



Notes: Authors' calculation based on EWCS 2015. Mean differences (in percentage points) in the incidence of task-related attributes by presence of ER. Monotone="Monotone tasks"; High speed="Working at high speed most of the time"; People="Dealing with people"; Customers: "Visiting customers or clients"; Influence="Influencing important decisions most of the time"; Own ideas="Applying own ideas most of the time"; Problems="Solving unforeseen problems"; Complex="Complex tasks"; Teams= "Teamwork"; Learning="Learning new things".

Figure A.2.2: Distribution of automation risk 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 (Denmark, Finland, Norway, Sweden); Centre-West (Belgium, Germany, Luxembourg, Netherlands, Austria, Slovenia); South (Greece, Spain, France, Italy, Portugal); West (Ireland, Malta, Cyprus, UK); Centre-East (Bulgaria, Czech Republic, Estonia, Latvia, Lithuania, Hungary, Poland, Romania, Slovakia).