

RISKS TO JOB QUALITY FROM DIGITAL TECHNOLOGIES: ARE INDUSTRIAL RELATIONS IN EUROPE READY FOR THE CHALLENGE?

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We examine the job quality effects of new digital technologies in Europe, using the framework of seven job quality ‘domains’: *pay, working time quality, prospects, skills and discretion, work intensity, social environment and physical environment*. The theoretical effects from new technology are ambivalent for all domains. Data on robot shocks matched to the European Working Conditions Surveys for 2010 and 2015 is used to generate empirical estimates, which show significant aggregate negative effects in three domains, and a positive effect in one. Some negative effects are enhanced where there is below-median collective bargaining. In light of these analyses, and in order to think through the challenge of regulating the development and implementation of all forms of digital technologies, we review regulations in several European countries. Drawing on the principles of human-centred design, we advance the general hypothesis that worker participation is important for securing good job quality outcomes, at both the innovation and adoption stages. We also consider the application to the regulation of job quality of national and supra-national data protection legislation. In these ways, the paper extends the debate about the future of work beyond employment and pay, to a consideration of job quality more broadly.

The empirical exercises were executed by Milena Nikolova and are based on the methodology in the working paper “Robots, meaning and self-determination” by M. Nikolova, F. Cnossen and B. Nikolaev. All authors belong to the Excellence Network of stakeholders at Bruegel, through its project Future of Work and Inclusive Growth. Francis Green acknowledges funding support from the UK Research and Innovation, Grant ES/W005271/1. David Spencer acknowledges funding support from the UK Economic and Social Research Council, Grant ES/S012532/1.

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Recommended citation:

Berg, J., F. Green, L. Nurski and D. Spencer (2022) ‘Risks to job quality from digital technologies: are industrial relations in Europe ready for the challenge?’ *Working Paper 16/2022*, Bruegel

1 Introduction

Since before the first industrial revolution, social science has concerned itself with the relationship between new technologies and the transformation of work, with accompanying anxieties surrounding the volume and quality of work (Mokyr *et al*, 2015). More recently, the rise of computerisation, ICT and the internet in the late twentieth century have become the foundation in the twenty-first century of the 'Fourth Industrial Revolution'. Digital automation is the main driving force, using artificial intelligence (AI) and machine learning to enhance prediction, and capitalising on the collection of 'big data' and the exponential growth of computing power (Agrawal *et al*, 2019; Spencer and Slater, 2020).

There has been substantive debate about the implications of the use of new digital technologies for current and future labour demand and wages. The character of digital technologies is seen as important in determining their employment effects (Acemoglu and Restrepo, 2019a, 2019b). Technology that is labour-saving will lead to higher unemployment in particular sectors and industries (the 'displacement effect') and lower wages; such adverse effects are part of a broader portfolio of societal risks, including greater inequality and impaired political discourse (Acemoglu, 2021). By contrast, technology that is labour-augmenting and productivity-enhancing (the 'productivity effect') will add to the number of tasks performed by workers and will stimulate new job creation (the 'reinstatement effect'), thereby supporting an economy with high employment levels. Many and varied forecasts have been made of how technological change will in practice affect employment growth, wages and inequality (eg Frey and Osborne, 2013; Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020; Arntz *et al*, 2016; Aksoy *et al*, 2021). Yet for all scenarios the response proposed in the dominant narrative – led by a broad range of consultants, thinktanks, scholars and international organisations – is that digital automation is best managed by the upskilling of workers (Schlogi and Prainsack, 2021).

However, there has been little debate on, or study of, the effects of new technologies on non-wage aspects of job quality (Min *et al*, 2021; Nurski, 2021; Menon *et al*, 2019; Smids *et al*, 2020). Robots and AI might be expected to affect both extrinsic aspects of job quality that attach to the labour contract – such as working time – and intrinsic domains associated with the work itself – such as worker autonomy. Such potential effects are distinct from, and may be only loosely related to, wage rates through the competitive mechanism of compensating wage differentials. This paper investigates potential effects, both positive and negative, of new digital technologies in the current era for job quality in multiple domains, and reviews emerging regulatory responses.

Given that all domains of job quality are important for worker well-being and health (Eurofound, 2019), the lack of debate about new technology and job quality is perhaps surprising. Moreover, the issue is emerging rapidly, with widespread evidence of recent expansion in the use of digital technologies. Robot use, for example, rose steadily from the mid-1990s in the United States, Western Europe and China (Acemoglu and Restrepo, 2020; Cheng *et al*, 2019). The deployment of AI systems in the United States, already growing rapidly since at least 2010, accelerated from 2016 (Acemoglu *et al*, 2021). This paper focuses on Europe. According to Eurofound's 2019 European Company Survey, 54 percent of establishments purchased software in the three years preceding the survey that was specifically developed or customised to meet their needs, while 51 percent of establishments were using data analytics for process improvements, monitoring employees or both. The use of robots specifically was highest in industrial sectors at 22 percent of establishments. The survey confirmed that, while digitalisation has proceeded at varied rates across European countries, it is assuredly increasing at pace. Over half of establishments were found to be increasing their deployment of data analytics. Eurofound's European Working Conditions Survey (EWCS) confirmed that, among the general European workforce, ICT had by 2015 established itself increasingly as part of everyday work life, with 56 percent of workers using ICT devices in some form for at least a quarter of their working time, up from 36 percent a decade earlier (Eurofound, 2017, p.85). According to the UK Skills and Employment Survey (Inanc *et al*, 2014), by 2012 three quarters of British workers were working with computers or automated equipment¹. With the onset of the COVID-19 pandemic, the deployment of digital technologies and internet communication for monitoring workers accelerated: for example, employers have started requiring employees to regularly disclose information on health status, and have deployed technologies such as GPS, radio-frequency identification, sensor and even facial recognition technologies (Ponce del Castillo, 2020; ILO, 2021).

Acemoglu (2021) argued that, without intervention, this expansion of AI-driven innovation risks becoming too much centred on automation and the displacement of labour, rather than on raising productivity through balancing automation with human-friendly tasks. Where there are economies of scope, automation that removes tasks from humans reduces their productivity in complementary tasks and is linked to deskilling. And in the context of labour management, AI risks being used excessively for enhancing monitoring of effort because this excess shifts rents from workers to employers – the risk in this case is lower wages plus higher economic inequality. Going beyond wages, however, we suggest in

¹ Authors' analysis of publicly available data.

this paper that whether the outcome of new digital technologies is beneficial or detrimental depends at least in part on factors influencing the balance of power in workplaces.

Section 2 delineates the seven domains that have emerged in the European discourse on job quality. Section 3 then considers the potential effects of new digital technologies in each domain. In Section 4 we present evidence of the effects of one particular form of new technology – robots – on these seven domains at the aggregate level across Europe. While recognising that effects will vary over time and space, our findings reinforce fears about potential detriment effects on job quality. One caveat is that our results are based on aggregate data; more detailed analysis – beyond the scope of this paper – is needed (eg using case-studies) to explore the effects on job quality of different kinds of robots and other digital technologies. That said, our findings are illustrative of the broader effects of robots and provide a useful input into ongoing academic and policy debates in the field. In section 5, we consider the challenge of regulation in defence of job quality. Reviewing developments across several European countries, and drawing on the principles of human-centred design, we advance the general hypothesis that worker participation is important in both innovation and adoption of digital technologies, while also discussing the application of national and supra-national data protection legislation to this issue of job quality. As a general point, we stress how the participation of workers in the design and implementation of digital technologies is needed to ensure the benefits are fully realised and shared equally in society.

2 Job quality and its domains

The concept ‘job quality’ comprises those characteristics of a job² that normally contribute to allowing workers to fulfil their material, social and psychological needs from paid work³. We begin in this section by contextualising the concept, its domains and their measurement within the evolution of public and scholarly discourse surrounding employment quality in recent decades. Job quality is an important component of ‘decent work’, which has, since 1999, formed one of the core organising principles for the International Labour Organisation’s monitoring and policy frameworks (ILO, 1999). Decent work is understood as productive work for women and men in conditions of freedom, equity, security and human dignity. In addition to considerations about the quality of the job itself – right to freedom of association and collective bargaining at work, safe and healthy workplace, and freedom from discrimination – decent work encompasses societal measures such as the proscription of child or

² While outside the scope of this paper, we note that the quality of unpaid domestic labour is also likely to be affected by new digital technologies.

³ Recent literature includes the need for meaningful work (eg Smids *et al*, 2020).

forced labour, the provision of social insurance, and overall labour market characteristics such as the unemployment rate. It has been incorporated within the broader framework of the United Nation's Sustainable Development Goals⁴.

Job-quality scholars agree broadly on to what characteristics of jobs are part of job quality, and should therefore be monitored with consistent indicators. For any domain (set of similar characteristics) to be included, there should be a good reason why it helps to meet the needs of workers; if not self-evident that reason should be supplied by robust empirical research. This condition is fulfilled by the classification proposed by the European Foundation for Living and Working Conditions (Eurofound), which includes three extrinsic domains (all aspects of the labour contract) and four domains intrinsic to the nature of the work (Eurofound, 2012). This typology was endorsed by a European Parliament resolution in 2016 for the purposes of analysis and monitoring of socio-economic and policy developments (European Parliament, 2016):

Extrinsic:

- *Earnings*. Monthly earnings measure the extent to which jobs meet workers' material living needs.
- *Working time quality*. The features of working time relevant to workers' needs include overall duration, timing and flexibility. High-quality working time means avoidance of very long working hours, flexibility for workers to have some control over when to work, and minimisation of working shifts such as night shifts that are known to be detrimental to health.
- *Prospects*. Good prospects are found in jobs which offer high job security and the potential for future earnings growth.

Intrinsic:

- *Skills and discretion*. High-quality jobs utilise workers' skills well, deploy higher level skills in complex jobs, provide training, and allow significant autonomy, including good opportunities for employees to organise their work and influence the tasks they are performing.
- *Work intensity*. Distinguished from working time, work intensity refers to "*the rate of physical and/or mental input to work tasks performed during the working day*" (Green, 2001, p.56). A high-quality job minimises the extent to which the work is highly pressurised, with intensive tasks needing to be done at high speed or to pressing deadlines with few pauses.

⁴ See www.un.org/sustainabledevelopment/wp-content/uploads/2016/08/8_Why-It-Matters-2020.pdf.

- *Social environment*. A positive social environment fosters support from co-workers and from line managers, and an absence of abusive experiences, such as verbal abuse, threats, humiliating behaviour, physical violence, bullying or sexual harassment.
- *Physical environment*. High-quality jobs are ones that avoid health risks, including many forms of environmental hazard and posture-related vulnerabilities.

One potential further domain remains contentious: the extent to which a job permits participation in organisational decision-making (Green, 2021). Some research shows that participation contributes directly, in itself, to worker well-being (eg Bartling *et al*, 2014; Gallie *et al*, 2017). Eurofound includes in the *skills and discretion* index the opportunities individual workers have to influence their own job tasks. However, wider participation – whether representative or otherwise – is not covered; the OECD has taken a similar approach (OECD, 2017, 13-14).

Indicators have been developed by Eurofound, and consistent data collection means trends have been measured for some domains from 2000 onwards (and from earlier for a small range of countries) (Eurofound, 2012, 2017)⁵. One common finding is the ubiquitous presence of a gender gap in earnings, with men earning more than women, while by contrast in almost all countries the physical environment indicator is higher for women than for men, reflecting lower exposure to physical risks. For other domains, the gender gap varies among countries. Across Europe as a whole, job quality has trended modestly upwards in three domains – *working time quality*, *physical environment*, and *skills and discretion* – while others have shown remarkably little movement over time (Eurofound, 2017). Apart from the Earnings indicator, all other domains show little or no correlation with conventional measures of affluence, such as GDP *per capita*. Moreover, there are substantial differences and contrasting time trends in job quality between countries. For example, the range of country means is approximately one standard deviation, in the case of *working time quality*, *work intensity*, *skills and discretion*, and *prospects*. Nordic countries do well in respect of *skills and discretion*, while France performs poorly in the domains of *work intensity*, *social environment* and *physical environment* (Green, 2021).

⁵ Most research at the macro level now also agrees that job quality should be measured using only objective indicators (even if sometimes reported by individuals), rather than by including subjective evaluations such as job satisfaction, but for a contrasting perspective on qualitative research, see Findlay *et al* (2013) or Jenkins and Chivers (2021).

3 The effects of digital technologies on job quality

Using the above typology of job quality domains, and drawing on multi-disciplinary theories, this section asks whether the new technologies of the current era have either a positive or a negative relationship with each domain. Indicative evidence from prior research is presented where available. Our analysis draws on but differs from that of Parker and Grote (2020) who organised a similar discussion and review of some intrinsic aspects of job quality through the prism of job-design theory and its associated categories⁶. Here, the analysis encompasses both extrinsic and intrinsic domains of job quality. A fundamental common point is the perspective that outcomes are not pre-determined, but are instead dependent on choices made in the design and implementation of new technologies – including in the use of AI – as well as on the organisational context and regulatory conditions under which they are permitted to be deployed.

Table 1 summarises the effects for each domain. Earnings, through the attentions of economists, is the domain for which there is most evidence on links with new technologies. The use of digital technologies can help create greater demand for certain human skills, such as those related to the development, maintenance and operation of the said technologies. Software designers, for example, may enjoy higher pay. In general, if digital technologies raise skill requirements in jobs, they will create the possibility for higher wages (Acemoglu and Restrepo, 2019a, 2019b). An increase in real earnings may also arise from lower prices linked to the positive productivity effect of new technology. Germany is one example where investment by firms in new digital technologies between 2011 and 2016 was found to be related to higher pay (Genz *et al*, 2019). Where the effect of digital technologies is to displace workers from tasks that become automated, they reduce the demand for workers engaged in those tasks, pushing down wages. Also, by making some skills obsolete, digital technologies can erode wages in those jobs: a classic case of deskilling and cheapening of labour. Increasing the reach of competition in the labour market, for example via the rise of online digital platforms, which has allowed employers to outsource tasks to workers located elsewhere, places further downward pressures on wages (Bergvall-Kåreborn and Howcroft, 2014). Digital technologies also facilitate closer surveillance of workers, thereby lowering the efficiency wages required to ensure effort compliance (Acemoglu, 2021). De Nardis and Parente (2022) listed several studies with varied implications for wages, and their own evidence covering

⁶ Baltrich *et al* (2021) reviewed (mainly) experimental studies of the effects of human/robot collaboration – an infrequent but emergent paradigm – using an ergonomic lens, on certain job-quality related factors (cognitive workload, trust in robots, satisfaction with robots, and ‘fluency’).

France, Germany, Italy and Spain suggested a negative association, as does the evidence on robotisation in the US (Acemoglu and Restrepo, 2020).

Table 1: Potential impacts of digital technologies on domains of job quality

Job quality domains	Positive impact of digital technologies	Negative impact of digital technologies
Earnings	<p>Digital technologies create a demand for some human skills pushing up wages for workers with those skills.</p> <p>The productivity benefits of digital technologies could be shared with workers through lower prices.</p>	<p>Following displacement, the relative abundance of labour for some jobs can exert downward pressure on wages.</p> <p>Digital technologies can also lead to deskilling in jobs, eroding wages.</p> <p>Digital technologies facilitate the rise of ‘gig-work’, which increases competition among workers; especially for work conducted online, they allow a widening of the pool of available workforce beyond national borders, potentially leading to a ‘race to the bottom’ in wages.</p> <p>Digitalisation improves employers’ capacity to monitor workers, lowering ‘efficiency wages’.</p>
Working time quality	<p>Digital technologies might automate tasks previously undertaken by humans in unsociable hours.</p> <p>Digital automation enables temporal and spatial flexibility to more closely match workers’ hours preferences</p>	<p>Digital technologies facilitate a closer connection for workers to work, which can be exploited to extend hours of (unpaid) work.</p> <p>‘Digital scheduling’ of tasks may increase or decrease work hours independent of workers’ preferences.</p> <p>‘Digital nudging’ for platform workers to work longer hours.</p>
Prospects	<p>If digital technologies are skill-enhancing, they can create opportunities for progression.</p>	<p>If digital technologies are skill-reducing, they reduce chances of promotion.</p> <p>Gig work increases job insecurity.</p>
Skills & discretion	<p>Digital technologies boost the displacement of humans in routine tasks.</p>	<p>Digital technologies can render workers’ cognitive skills obsolete. They can also reduce workers’ autonomy by increasing monitoring (e.g. via types of ‘algorithmic management’).</p>
Work intensity	<p>Digital technologies take on tasks that require the most intensive hard work.</p>	<p>Digital technologies are effort-biased: enabling more intensive work, and lowering the cost of close monitoring.</p>
Social environment	<p>Digital technologies can facilitate positive social interaction in work by automating drudgery</p>	<p>With digital technologies as co-workers, the scope for human workers to interact socially is reduced – work becomes more alienating.</p>
Physical environment	<p>Safer and more healthy work environments may be created as digital technologies take on dangerous, dirty and health-limiting work</p>	<p>Potential injuries from technological malfunctions.</p>

Working time quality could also be improved by digital technologies. Such technologies might be configured to reduce employers' needs for unsociable shifts (including night working), adding to working time quality. Platform working technologies may allow greater working time flexibility under workers' control (Chen *et al*, 2017), including the potential to concentrate working hours into four days. Stimulated by the pandemic, digital technologies have also enabled the reconfiguration of work locations and spaces (Felstead, 2022), curtailing commuting time. Yet, this facility of new technologies to make working time and space more flexible can have negative effects. Digital technologies can create an 'always-on' culture, by providing ready access to, and a near permanent connection with, work. Smartphones, for example, have become a way for workers to remain contactable by work supervisors, seemingly around the clock, leading to problems of overwork or underpayment for work hours. At worst, work may come to colonise home-life and erode free time (Wajcman and Rose, 2011; Shevchuk *et al*, 2019). 'Digital scheduling' (forms of scheduling made possible by new digital technologies) can also be used by employers to extend hours of work (eg Moore and Hayes, 2018). 'Digital nudging' may encourage platform workers to continue working when it is time for rest (Scheiber, 2017).

Prospects may be improved by digital technologies where they generate jobs with rising skill requirements and a rising wage profiles. When firm-specific skills requirements are raised, workers working with robots could expect improved promotion prospects. Conversely, when digital technologies displace skilled production tasks, *prospects* would diminish. *Prospects* are also reduced by job insecurity, which could be worsened by new digital technologies. The most frequently cited example here is the rise of 'gig-work' (Berg *et al*, 2018; Cirillo *et al*, 2021). Applications developed by gig-economy platforms facilitate the immediate hiring of workers for one-off tasks, reducing the incentive for firms to hire workers on traditional employment contracts.

Turning to the intrinsic domains of job quality, *skills and discretion* may be augmented by digital technologies, which in principle can facilitate decentralised decision-making. If robots take on mundane tasks, what remains is the more skilful and autonomous work. If digital technologies are used to augment human productivity rather than to automate, the resulting jobs may require new skills (Daugherty and Wilson, 2018), and working with these technologies may help to make work more meaningful (Smids *et al*, 2021). Conversely, when digital technologies replace the more interesting and challenging aspects of work, *skills and discretion* will decline. Autonomy may also be impaired by over-controlling decision-making systems, or by forms of 'algorithmic management' in which data is gathered that invades data privacy and is used to monitor, assess and control the behaviour of workers (Kellogg *et al*, 2020). Whether the meaningfulness of work is increased or reduced by digital technologies

ultimately depends on whether technologies are designed to replace or support skill levels and autonomy (Smids *et al*, 2021).

If digital technologies are designed to take on the most intensive aspects of work, workers could be given a more balanced pace of work. Yet previous studies have found that computer use at work has been 'effort-biased': both facilitating greater *work intensity* by enabling work to be delivered most efficiently to the worker at all times, and enabling the close monitoring of effort by managers with associated penalties for working slowly (Green, 2006; Green *et al*, 2022), though in Menon *et al* (2019) the effect is small and statistically insignificant. Digital technologies including robots and systems of algorithmic management offer possibilities to augment these same processes (Gilbert and Thomas, 2021). Antón *et al* (2020) presented some European-level evidence that, prior to 2005, robots had had a detrimental effect on *work intensity*. Digital scheduling intensifies the pace of work while working. Technology-enabled remote working potentially also raises *work intensity* (Felstead and Henseke, 2017).

The *social environment* of work could also be improved by digital technologies. Where they remove drudgery from jobs and create more scope for human interaction at work, they will enhance the *social environment*. In contrast, if human workers are required to work mostly with digital technologies and lose the opportunity for human interaction and social support, they may experience work as more alienating. For example, knowledge management systems (KMS), while providing back-up for absent workers and making jobs more accessible for untrained workers, reduce the need for knowledge-sharing between colleagues and thus also reduce human interaction. Control of workers by technology will lead to situations in which work is more socially isolating. For those working via online platforms, indeed, work may become a lonely endeavour (Parker and Grote, 2020). Digital technologies also increase the opportunity for online pressure or bullying. Uber drivers, for example, have faced trial by ratings, leading to instances of discrimination and account deactivation (Rosenblat *et al*, 2017).

In respect of the *physical environment* of work – the final job-quality domain – in principle a well-designed robot work system might help reduce health risks by taking on dangerous, dirty and health-limiting work, such as assisting in nuclear waste disposal. Many 'Operator 4.0' technologies have the goal of enhancing the physical well-being and safety of workers. Examples include exoskeletons, AR/VR applications and (biometric) wearables (Romero *et al*, 2016). But there are also risks if the design of robot work systems fails to embed the health and safety of attendant workers. Digital technologies that malfunction may have devastating effects. Parker and Grote (2020) provided examples of unintended consequences from sub-optimal, 'techno-centric' work design that fails to incorporate the perspective

of technology users. Automated Amazon warehouses have also been criticised for their harsh and health-limiting physical environments (Sainato, 2020).

In sum, this review shows that digital technologies have the potential to improve job quality in many dimensions, but also to make it worse. Our analysis points, therefore, to an uncertain future for job quality as deployment of these technologies accelerates, with associated promises and risks for health and well-being. In determining job quality outcomes what may be important is the form taken by the technology – in particular, whether it has been designed to be “*human-centred*” (Parker and Grote, 2020)⁷. Such an outcome would be unlikely in an unregulated market. It can be suggested that a key factor in determining the forms of innovation and adoption of new technologies is the balance of power between labour and capital, which depends in turn on opportunities for participation. Where labour is empowered, whether through unions or works councils at firm level, or through industry-level regulation in which the participation of social partners is embedded through political and institutional channels, it can affect both the form of the innovation and the design of jobs. We consider potential responsive regulatory practices in section 5.

4 The impact of industrial and service robots on job quality in Europe

To begin to examine the potential risks in practice, this section investigates job-quality outcomes at the aggregate European level of one particular form of digital automation in recent years: robots. Robots are used across the economy, though are concentrated in certain industries, especially automobiles and transport. The usefulness of this aggregate-level analysis, made possible by the availability of Europe-wide survey data, is that it will indicate where there are dominant effects, that is, where the balance of positive or negative effects falls clearly on one side.

Specifically, we investigate empirically whether the shock of accelerating automation in the recent decade through the use of robots is a risk to job quality, using data from the 2010 and 2015 EWCS. We use the job-quality indices constructed by Eurofound (2012) for each of the seven job-quality dimensions based on these two survey waves (see the Appendix for more detail on these measures and their summary statistics). We match industry-level information on robot stocks from the International Federation of Robotics for 13 industries (which is available for a large sample of countries and industries from the mid-2000s), data on the fixed capital stock in computing, communications, computer software

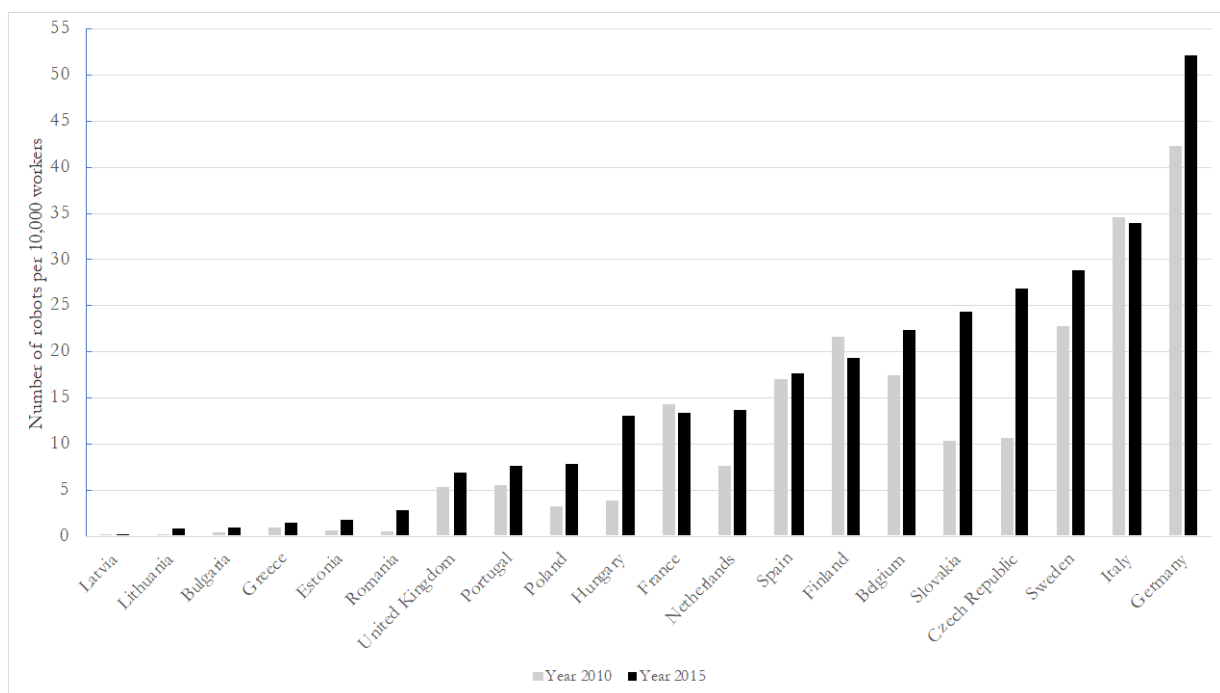
⁷ Human-centred design is also important for workers to ‘accept’ the technology and actually use it.

and databases from EU KLEMS⁸, and information on the number of employees in each industry in 20 European countries in 2005 from EU KLEMS.

The data is at a high level of aggregation. This means that we are unable to differentiate between different types of robots (eg co-bots and boxed robots). We also cannot look at the effects of other types of digital technologies. Further analysis using different datasets and incorporating case studies would be needed to address and disentangle these effects. Our empirical analysis of robot data is therefore illustrative of wider effects and we recognise that scientific and policy debate would benefit from more empirical studies.

The data shows the expanded use of robots, while also demonstrating that the rate of adoption of robots varies greatly between countries. Figure 1 shows Germany in advance of other countries, with Italy and Sweden following behind, while eastern European countries Latvia, Lithuania and Bulgaria have the lowest robot intensity. In most countries, the period between 2010 and 2015 saw ongoing penetration of robots in workplaces throughout the economy.

Figure 1: Industrial robots per 10,000 workers, by country and year



Source: Bruegel based on IFR and EUKLEMS.

⁸ See <https://euklems.eu/>.

Our methods

To measure the shock of automation, we follow Aksoy *et al* (2021) in using for our key independent variable the inverse hyperbolic sine transformation (IHS) of the change in the number of multipurpose industrial robots per 10,000 workers, in the industry where the job is located. This shock is defined, for each industry and survey year separately, as:

$$Robotisation = IHS \left[\frac{num.robots_{t-1}}{10,000 employees_{2005}} - \frac{num.robots_{t-5}}{10,000 employees_{2005}} \right] \quad (1)$$

where t denotes survey year (ie 2010 or 2015). The IHS is used because the distribution of the changes in robotisation variable is highly skewed. We decided to use a lag of one year because the consequences of automation shocks are not contemporaneous. Lagging the key independent variable also mitigates issues of reverse causality. The shock period is then specified as the period since the previous wave⁹. We normalise the change in robotisation by the number of workers in 2005, which is a constant base year and ensures that the changes in the robot stock are independent of changes in the number of employees.

Our dependent variables are the job quality indices, as defined in section 2. All indices are summative composites of multiple items for each domain covering closely-related working conditions, as specified in Eurofound (2012); for more details see the appendix.

In order to estimate the effects of robotisation on a job held by individual i , for each of the seven domains (j) of job quality, in year t and country c , we estimated equation (2), which regresses the index against the introduction of robots and a number of controls:

$$JobQuality_{i,c,j,t} = \beta_0 + \beta_1 \Delta Robotization_{i,c,t} + \alpha Controls_{i,c,t} + \delta_t + \mu_c + \varepsilon_{i,c,j,t} \quad (2)$$

where robotisation is the change in robotisation as defined in equation (1) above, δ_t denotes time fixed effects (a dummy variable for 2010 or 2015 survey year), μ_c denotes country fixed-effects, and $\varepsilon_{i,c,j,t}$ is the stochastic error term. Controls include age group, gender, hours of work, education, occupation, company size and a measure of ICT capital (included because it might be correlated with robotisation)¹⁰. The motivation for including time dummies is that the adoption of technology, including automation, is often pro-cyclical (Anzoategui *et al*, 2016; Leduc and Liu, 2021), as might also be workers' reports of job

⁹ For survey year 2015, the shock is calculated between 2014 and 2010, while for survey year 2010, the robotisation shock is calculated between 2009 and 2005.

¹⁰ The inverse hyperbolic sine transformation of changes in ICT capital; see the appendix.

quality. Finally, the country-specific dummies are included to account for different labour-market policies and institutions across countries. We report robust standard errors, clustered at the country and industry level. All regressions are weighted using the survey weights¹¹.

Any estimates of β_1 obtained from a linear Ordinary Least Squares regression could not be validly interpreted as causal effects of introducing robots, because the introduction of robots may be endogenous. For example, there may be industry-specific shocks prompting firms to both adopt robots and take other measures that also affect job quality. In addition, workers may choose to work in particular industries because of unobserved individual traits and idiosyncrasies, including industry-specific skills or differences in ability, which might also be related to their job quality. To mitigate against this issue and to identify causal effects, we rely on an instrumental variables technique, whereby we instrument our robotisation measure with the change in the average robot stock per worker in the same industry across all other countries in the sample. The measure is similar to the instrument used by Acemoglu and Restrepo (2020) and was also used in Anelli *et al* (2019). The main assumption behind this instrument is that the industry-level adoption of automation in other countries is exogenous to the respondent's job quality.

The first-stage regressions of the instrument, and a table of the job quality measures for 2010 and 2015, are in the appendix.

Findings

Table 2 shows our findings. Panel A shows the estimated effect of robotisation, using Ordinary Least Squares, while Panel B presents the IV estimates. The two sets of estimates are consistent in that the same coefficients are found to be statistically significant with consistent signs. The magnitudes of the IV estimates are, however, greater, suggesting that selection endogeneity biases downwards the conditional associations of robot shocks with job quality. The coefficients imply that the job quality consequences of robotisation across Europe were predominantly negative in this period. Specifically, robotisation lowered *skills and discretion* and *working time quality*, and increased *work intensity*. In mitigation, however, there is a weakly significant positive effect of robotisation on *prospects*. There were no significant impacts on either the *physical environment* or the *social environment*, or on *earnings*. To see the magnitude of these effects, we computed the implied elasticities (following Bellemare and Wichman, 2020), which are relatively modest. For example, a 10 percent increase in robotisation

¹¹ The survey comes with precalculated weights to make the sample representative for the total workforce within and across countries and time.

corresponds to a 0.2 percent decrease in the *skills and discretion* index, a 1 percent decline in *working time quality*, and a 4 percent increase in *work intensity*. Nevertheless, given that the mean value of the job quality indices did not change all that much during the analysis period, in which the robotisation shocks were considerable (for example, averaging 73 percent in 2010 among industries with initially non-zero robots), the magnitudes of the coefficient estimates, though small, are notable. They represent an aggregate of positive and negative effects on multi-item indices.

Table 2: The effect of robotisation on job quality

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	<i>Monthly earnings</i>	<i>Prospects</i>	<i>Working time quality</i>	<i>Skills & discretion</i>	<i>Work intensity</i>	<i>Social environment</i>	<i>Physical environment</i>
Panel A: Ordinary Least Squares Estimates							
Robotisation	3.658	0.285*	-0.285**	-0.562***	0.553***	-0.065	-0.099
	(4.171)	(0.155)	(0.126)	(0.193)	(0.178)	(0.187)	(0.102)
Elasticity	0.003	0.005	-0.003	-0.009	0.013	-0.001	-0.0012
R ²	0.513	0.146	0.638	0.248	0.176	0.049	0.334
Panel B: IV Estimates							
Robotisation	10.129	1.043***	-0.800***	-1.493***	1.727***	-0.436	-0.030
	(7.456)	(0.383)	(0.278)	(0.364)	(0.392)	(0.413)	(0.216)
Elasticity	0.008	0.017	-0.009	-0.023	0.040	-0.005	-0.0004
R ²	0.513	0.142	0.637	0.245	0.170	0.048	0.334
1st stage F-stat	118.2	35.19	111.5	111.5	111.8	34.04	111.5
Panel C: IV Estimates							
Robotisation	15.310	0.552	-1.332***	-2.474***	1.937***	-1.314*	-0.393
	(11.529)	(0.461)	(0.464)	(0.560)	(0.577)	(0.709)	(0.321)
Collective Bargaining Above Median	70.369*	-3.378**	-1.828	-2.213*	-7.370***	-3.119*	1.895*
	(42.362)	(1.699)	(1.112)	(1.310)	(2.035)	(1.707)	(1.113)
Robotisation X collective bargaining above median	-8.972	0.865	0.901*	1.665***	-0.388	1.556**	0.627
	(13.682)	(0.698)	(0.504)	(0.644)	(0.690)	(0.776)	(0.397)
1st stage F-stat	35.34	6.665	34.42	34.42	34.73	6.426	34.41
Mean of the dependent variable	1271.488	61.835	85.259	63.193	41.979	79.368	78.888
Number of observations	13,091	8,579	17,746	17,745	17,687	7,831	17,745

Source: Bruegel based on IFR, EUKLEMS, ILO, and European Working Conditions Surveys (2010, 2015). Notes: The table reports results from OLS and IV regressions of various indices of job quality on robotisation, by the level of collective bargaining coverage in the respondent's country of residence. Robotisation is measured as the inverse hyperbolic since transformation in the number of robots per 10,000 workers. All regressions include a constant and country and year fixed effects, and the following demographic and job controls: age group, gender, hours of work, education, occupation, company size, and the inverse hyperbolic sine transformation of changes in ICT capital. All regressions include two-way clustered standard errors at the country and industry levels. Monthly income is PPP-adjusted and in euros, winsorised at the 1 and 99 percentiles to minimise the role of outliers. The rest of the job quality indices are measured on a scale of 0 to 100. No information is available for the prospects and social environment indices for 2010. The instrumental variable in Panel B is based on the industry adoption of automation in all other countries in the sample (except that particular country). The mean of the dependent variable is calculated based on the observations used in that particular analysis sample. All regressions are weighted using the survey weight. The analysis sample is based on 20 European countries (see Figure 1) and 13 industries. *** p<0.01, ** p<0.05, * p<0.1

A limitation of these aggregate-level estimates is that effects may vary across countries with different regulatory institutions and protections for workers. The estimates in Panels A and B, therefore, should be seen as encapsulating an average of these effects. Unfortunately, the sample sizes present in the EWCS are insufficient to yield reliable and precise estimates at disaggregated levels. Nevertheless, staying with aggregate estimates, we are able to conduct a simple test of whether collective bargaining coverage might cushion some of the negative consequences of robotisation, given that such coverage might directly or indirectly affect how robots are used in workplaces. We interact robotisation shocks with a dummy variable indicating whether there is a high level (ie above the median) of collective bargaining coverage in the industry.

The estimates in Panel C, again using the IV procedure, suggest that the negative effects on *skills and discretion* and on *working time quality* are exacerbated in industries with low collective bargaining coverage. Moreover, where there is low collective bargaining coverage, there is also a negative effect of robotisation on the *social environment*. In contrast, the work intensification effect of robots is not significantly mitigated by the collective bargaining coverage and the positive relationship with *prospects* becomes imprecise.

The limits of the data can be highlighted once more. For example, we cannot deal with the mediating effects of management style (supportive vs directive) and organisational structure (hierarchical vs team-based) in cases where robots are implemented. To do this, we would need employer-level data. There is evidently more scope to develop the analysis via other data and methods (eg case-studies). Nonetheless, the above results offer insights into how robots, at the aggregate level, have affected different dimensions of job quality and how their impact is potentially mediated by country-level bargaining institutions. Indeed, the key finding that the effects of robotisation on job quality this century has until recently on balance been negative is striking. In particular, it suggests that new digital technologies may constitute a significant risk for job quality, and highlights a pressing need to examine the general role of regulation in conditioning their effects.

5 Worker involvement and regulation for a human-centred approach

This section considers the implications for policies and interventions to help improve job quality when new technologies are being developed and implemented, and reviews some recent developments in Europe. It is concerned, more directly, with exploring mechanisms and conditions that would ensure digital technologies are used and implemented in ways that raise job quality. As we highlight below, positive outcomes depend crucially on workers being able to participate in workplaces and to actively shape the innovation process.

The near-exclusive focus on skills upgrading, as the labour market policy response to new digital technology's effects on employment, has been criticised as neglecting consideration of income support or other redistributive policies, and as relying on a deterministic acceptance of new technology, and an unwarranted faith in supply-side skills policies (Schlogl and Prainsack, 2021). To these points we add that, in respect of technology's job quality effects, a simple reliance on worker reskilling would be wholly inadequate.

Rather, we consider two avenues for potential action. First, we suggest that worker participation in either the design or the application of technologies (or both), tipping the balance of power some way back towards those who work alongside the technologies, is the key to ensuring positive results with respect to job quality (Parker and Grote, 2020). Such participation is most likely to occur in countries where workplace consultation is already part of the industrial-relations system, most notably in the Nordic countries and Germany with its system of co-determination. Yet, participation is also possible in the absence of inclusive industrial relations systems: organisational structures that support teamwork, problem-solving and decentralised decision-making also empower workers and increase worker voice on technology. Workers in such organisations, with greater job security, can more easily voice concerns and make constructive suggestions about the application of technology. In this regard, there is a general case for worker participation. Second, supplementing multi-level participation, statutory regulations also have a role to play in shaping job quality vis-à-vis technology, especially if such regulations ensure workers' data privacy, give workers access to their data and put limits on monitoring, surveillance (for example, with workplace CCTV cameras) and algorithmic management (Hendrickx, 2019).

Engaging workers in the design of technological systems – prior to their implementation – can mitigate negative effects and also potentially improve outcomes for both job quality and productivity. The concept of 'human-centred technology' was developed in the 1970s and 1980s as an antidote to 'technology-centred systems', which, since the days of Taylor, have been guided by the conviction that

technology is superior to humans. In human-centred technology, “*the operator is considered an ‘asset’ rather than a ‘nuisance’*” (Hancke *et al*, 1990, p. 59) and the user is acknowledged as a source of knowledge and creativity that should be harnessed. Though the degree of involvement of the user in human-centred technological design varies¹², at its most inclusive, it relies on participatory design methods, with stakeholders involved in the design process to ensure that plans, implementation processes and results meet the various stakeholders’ needs (Simonsen and Robertson, 2013).

Employee participation in the process of technological innovation is found to improve outcomes through two main channels (Vereycken *et al*, 2021). First, workers are an important source of tacit knowledge about the production process, which improves the design and implementation of the technology. Second, involving workers increases their likelihood of accepting and productively using the new technology after implementation (Felstead *et al*, 2020). A case study of a German steel plant showed that participatory design can have significant effects in terms of technology acceptance and innovation outcomes (Kohlgrüber *et al*, 2019). Vereycken *et al* (2021) further noted that employee participation in both work organisation and technological innovation improves job quality; yet, there is still little evidence on the mediating role of formal employee representation structures (Belloc *et al*, 2022).

Having an official structure for employee representation – either a works council or trade union delegation – can be a useful way for employers to engage with workers in a human-centred technological design and application process. However, such a structure is only present in 29 percent of EU establishments, and not all company-level employee representation is involved in technological design and application (Eurofound and Cedefop, 2020). Some of the best practices come from the Nordic countries, which have a long tradition of participatory design (referred to as ‘cooperative design’). This has been used by trade unions since the 1960s to develop strategies and techniques for workers to influence the design and use of computer applications at the workplace (Asaro, 2000). In the mid-2010s, three German trade unions launched Arbeit 2020, a project aimed at preparing works councils to participate in shaping technological change associated with Industry 4.0¹³. The project trained work councillors on the potential impact of digitalisation through an analysis of full change processes induced by digitisation in an entire plant. The training sought to strengthen co-determination by improving the ability of work councillors to respond and negotiate workplace agreements on this issue with employers. As a result of the project, numerous agreements (called Agreements for the Future) were signed that included provisions for skills development, working-time flexibility, data protection,

¹² Asaro (2000) gave a history of the evolution of user-centred design methods, some of which are more participatory than others.

¹³ See <https://www.arbeit2020.de/>.

monitoring of employee performance, project management, corporate governance, health and safety and workload reductions, as well as the early involvement of works councils and employees in managing change (Bosch and Schmitz-Kießler, 2020; Haipeter, 2020). These provisions, it can be predicted, are likely to ensure that the outcomes for job quality are more favourable for workers.

Some enterprises without official employee representation may involve their workforces in managing technological adoption out of recognition of the benefits for productivity as well as job quality. Kelly and Moen (2020) is a recent example in the United States where job redesign improved job quality in a Fortune 500 company. In most instances, however, workers' feedback is not solicited before the technology is put to use. Depending on the technology, there may still be scope for adjustment at this late stage. Unsolicited feedback from staff is more likely to occur in high-engagement workplaces – those companies that regularly facilitate the direct participation of employees in organisational decision-making. According to the 2019 European Companies Survey, fewer than one-third (31 percent) of companies in the EU meet this criterion (Eurofound and Cedefop, 2020). The possibilities for employee feedback are less likely if workers are on temporary contracts, as job insecurity can keep workers from voicing opinions or concerns (Sluiter *et al*, 2020). In cases where union representation is absent, workers may be merely notified of changes in technology, with no opportunity for feedback. In low-engagement workplaces, technological change – from a worker perspective – is more likely to be viewed as a hostile and threatening force.

A particular focus for potential future engagement and negotiation, not yet widely embraced by unions, is the use of monitoring and surveillance through data analytics software and, relatedly, the growth in algorithmic management. Algorithmic management can range from the automated sanctioning and even dismissal of workers, as in the oft-cited case of Uber drivers being blocked from the application if their rating falls below a certain threshold (Rosenblat and Stark, 2016), to the use of scheduling software for designating workers' shifts in the retail sector or voice-picking software in warehouses. Yet, where consequences are foreseen and engagement takes place, technological systems can be designed to abide by laws or collective-bargaining agreements. For example, scheduling software can incorporate regulation on advance notice in its design, or monitoring systems can be rendered transparent so that workers are aware of their monitoring, have access to the data, and have avenues for redress in cases of dispute.

The growing digitalisation of workplaces has prompted trade unions to increasingly include monitoring and surveillance as well as workers' data privacy in collective agreements and other negotiations (Akhtar and Moore, 2016). Nevertheless, the use of collective agreements to address such issues differs

greatly across EU countries. In Italy, the ADAPT dataset¹⁴ revealed that just 4–8 percent of Italian company-level collective agreements between 2014-2018 included clauses regulating employee data processing (Dagnino and Armaroli, 2019). By contrast, data from the Hans Boeckler Foundation archive showed a different situation in Germany, with over 63 percent of works agreements including clauses on employee data protection in 2015, increasing to almost 70 percent in 2017 (Dagnino and Armaroli, 2019). The Italian and German workplace-level agreements also differ in character, in that the Italian agreements focus on the use and processing of data collected by new technologies and the reasons for their introduction, whereas in Germany the management of data tends to represent just one issue in a broader regulation related to the installation of a new device. Dagnino and Armaroli (2019) explain that the greater and more encompassing collective negotiation in Germany stems from the German Works Constitution Act (1972, last amended in 2001), which provides works councillors with the right to co-determination in the matters related to the introduction and use of technical devices to monitor employees' behaviour and performance. Unlike the Italian case, in Germany, if no agreement between workers and the employer is reached, a conciliatory procedure is activated that takes the place of the agreement between the employer and the works council. These procedural requirements are stricter than in Italy where, in the case of the failure to conclude an agreement, the employer can act unilaterally.

In other European countries, including Belgium and Spain, workers' representatives and trade unions have fewer information and consultation rights. In Belgium, there are collective labour agreements ('CAO') on data from cameras and electronic communication in the workplace¹⁵. In Spain, a new data protection regulation – updated in accordance with the EU's General Data Protection Regulation (GDPR, Regulation (EU) 2016/679) – was adopted in 2018, including specific provisions on data protection in employment contexts. However, it did not include binding procedural measures to enable its systematic implementation. On this basis, we would expect that job quality would have better outcomes from new technology in Germany.

While workplace consultation and negotiation are best suited for addressing issues of technological adoption in the workplace given the flexibility they allow, broad regulation such as the EU's GDPR is nonetheless useful in establishing safeguards, especially for workers in small and medium-sized firms that are less likely to be unionised (Johnston and Silberman, 2020). In particular, the GDPR constrains fully-automated decision-making by allowing the affected party to object to how their data is used, to be

¹⁴ <https://moodle.adaptland.it/course/view.php?id=299>.

¹⁵ See CAO 68 and CAO 81 and law

(https://www.ejustice.just.fgov.be/cgi_loi/change_lg.pl?language=fr&la=F&cn=2007032139&table_name=loi); also see: <https://blog.associatie.kuleuven.be/paradigms/data-op-de-werkvloer-en-de-rol-van-sociale-dialogo-eeen-kleine-stand-van-zaken/>.

informed about the use of data and to demand a human interface. Though its application to the employment context is not straightforward (Aliosi and De Stefano, 2021), there are already examples of workers asserting their data rights as a result of the GDPR, with Uber drivers in London, for example, suing to get access to their data (Lomas, 2020).

The European Commission's April 2021 proposal on the regulation of AI (European Commission, 2021) also aims to protect workers in the context of new technologies, by classifying workplace applications of AI as 'high risk' for the health, safety and fundamental rights of workers. According to the Commission, these systems "*may appreciably impact future career prospects and livelihoods of workers*" by "*perpetuating historical patterns of discrimination*", and violating "*rights to data protection and privacy*" (European Commission, 2021)¹⁶. The 'high risk' status means that workplace AI systems would be subject to strict obligations such as risks assessments and transparency measures. However, as the proposed regulation only requires *self assessment* by the provider of the system and the risks mentioned do not explicitly cover job quality beyond the health and safety of the worker, the extent to which this regulation provides sufficient protection is debatable¹⁷.

Along with the explosion of interest in and concern about the future of work comes an arguably greater awareness that technological forces cannot be left to the market, and that the active engagement of social partners and the state is necessary if outcomes for job quality are to be positive. Prompted by such trends, the European social partners signed a landmark framework agreement on digitalisation in June 2020¹⁸. The agreement acknowledged the significant contribution of digital technologies to security, health and safety, and efficiency, but stressed the risk that excessive data collection and monitoring will lead to deterioration of working conditions and well-being of workers. Indeed, if everything one does at work is tracked (emails, log ins, work speed, communication with one's trade union rep, use of social media and so on) data collection *per se* can lead to serious implications for many aspects of job quality. The framework agreement calls for regulation to minimise the amount of data that employers collect about their workers, for transparency, and for clear rules on the processing of personal data to limit intrusive monitoring and data misuse. The framework agreement also calls for the

¹⁶ European Commission, COM/2021/206 final, 'Laying down harmonised rules on artificial intelligence (Artificial Intelligence Act) and amending certain Union legislative acts', <https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A52021PC0206>.

¹⁷ See <http://global-workplace-law-and-policy.kluwerlawonline.com/2021/04/16/the-eu-proposed-regulation-on-ai-a-threat-to-labour-protection/>.

¹⁸ The full agreement is available at: <https://ec.europa.eu/social/main.jsp?catId=521&langId=en&agreementId=5665>.

involvement of worker representatives to address issues related to consent, privacy protection and surveillance.

The wider point of the above discussion is that the long-standing contentious issues of employee voice and workplace governance are likely to matter more than ever, and in new ways, as the Fourth Industrial Revolution unfolds. Workers are more likely to share in the gains, and less likely to suffer falls in job quality, if they have some say over how technology is used and deployed at work. Forms of workplace governance that are more participatory and inclusive, if they lead to greater acceptance of innovations at work, could also yield better outcomes for employers. The possibility of higher productivity alongside higher job quality could thus be realised if workplaces allow some degree of democracy, with, for example, workers on company boards and more directly engaged in innovation. A human-centred approach necessitates, ultimately, strengthening the voice of workers who will use the technology.

6 Conclusion

Our analysis suggests that debate about the effects of digital technologies should be moved on from a preoccupation with employment and pay to a consideration of job quality more broadly. Until quite recently the study of technology's effects on employment was virtually coterminous with the discourse on the future of work. The onset of the COVID-19 pandemic altered that, through its enforced change of working patterns with significant implications for working-time quality, work intensification and the social environment of work (ILO, 2021). Digital communication technologies were of course indispensable for these changes, many of which – such as hybrid working – appear set to endure following the collective learning that has taken place. Even apart from these shocks, however, the implications of new technologies for job quality merit closer attention.

Our analysis has shown that technology's effects are ambivalent: for each of the seven domains of job quality there are situations in which digital technologies may enhance working life, and others where the opposite may occur. Our estimates find that robotisation in the last decade has negatively, if modestly, affected job quality in the aggregate across Europe in three domains: *working time quality*, *skills and discretion*, and *work intensity*. Our estimates also suggest a role for institutions in that, where there is a below-median level of collective bargaining, robotisation has led to a decline in the *social environment* index, and the negative effects on *working time quality* and of *skills and discretion* are exacerbated. There are areas where the empirical analysis could be extended – for example, there is scope to explore further how workplace organisation affects the relationship between digital

technologies and job quality. Nevertheless, the estimated results suggest significant average effects of robots on job quality.

These new findings confirm the need for policies to secure good job-quality regulation, because of its effects on worker well-being and public health. Unfortunately, despite persistent rhetoric proclaiming the need for ‘more and better jobs’, job quality has yet to become a prominent target for policymakers within European employment ministries, or even to figure in a practical and non-rhetorical manner in the Employment Guidelines or the Joint Employment Reports issued by the European Union. Piasna *et al* (2019) attributed this failure to the fact that job quality policies lie in contested political terrain. ‘Flexicurity’ policies have continued to dominate the employment discourse, and European policy-formation institutions have yet to produce agreed indicators that could form the foundation for guidelines and regular policy evaluation. This particular gap becomes more serious when we consider how job quality is likely to be impacted by new digital technologies in the coming decade. In our final contribution, we have reviewed some regulatory developments across Europe aimed at limiting the techno-centric orientation of digital innovations and embedding the principles of human-centred design. Our discussion suggests that forms of worker participation, whether in design, innovation or application, are needed, perhaps more than ever, in the current and future workplace as digital technologies are rolled out.

Our paper has well-signposted limitations. The empirical analysis has been conducted at a high level of aggregation and with a limited range of variables, and we recognise that, given ambivalent theoretical expectations, there will be many instances of beneficial deployment of digital technologies, some with positive external benefits that also merit regulatory or financial support. Relationships may be non-linear, including potential interactions among job-quality domains, with deterioration in some domains partially compensated for (as economic theory suggests) by improvement in others. The effects of digital technologies will also be conditioned by institutional, organisational and regulatory contexts. Future research, we suggest, could usefully investigate the variation in digital technology effects across domains, sectors and nations, in order to build a comprehensive picture of where good regulation is needed.

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Appendix

This appendix contains further information about the data and analysis used in section 4.

1. Data

a) Robots and other technology.

We source data on multipurpose industrial robots from the International Federation of Robotics (IFR), which provides information on the number of the operational robot stocks per year, country, and industry, based on all global robot suppliers. Robot stocks are calculated assuming an average service life of 12 years and no use thereafter.

According to the IFR (2021), a multipurpose industrial robot is an *“automatically controlled, reprogrammable, multipurpose manipulator that is programmable in at least three axes, and either fixed in place or mobile, and intended for and typically used in industrial automation applications.”*

To calculate the measure of robotisation used in the paper, we use information on the number of employed persons per industry and country in 2005 from EU KLEMS. We also use information on the investments in data on the fixed capital stock in computing, communications, computer software and databases combined from EU KLEMS.

b) Job-quality data

We merge the robotisation data with worker-level data from the European Working Conditions Surveys for 2010 and 2015. Specifically, we rely on the UK Data Archive Study Number 7363 - European Working Conditions Survey Integrated Data File, 1991-2015, which has the calculated job quality indices. Different workers are polled each year and as such, the data are pooled cross-sections rather than a panel. The European Working Conditions Survey provides worker-level information in collected via face-to-face interviews with almost 44,000 working adults aged 15 years and older who work a minimum of one hour per week. Sample sizes range from about 1,000 to 3,000 per country.

We use information on workers in 13 industries and 20 countries (Figure 1), for which we have information in the IFR and EU KLEMS data. We exclude the ‘all other non-manufacturing’ industry and the armed forces. We also only keep individuals with one job. We drop observations with missing information on industry.

While the EWCS has been conducted since 1991, we are limited in the number of years of survey data we can use because of the robotisation measure. This is mainly why we only include surveys from 2010 and 2015 in our analysis.

Our dependent variables are the job quality indices, as defined in section 2. All indices are summative composites of multiple items covering closely-related working conditions. For example, *physical environment* incorporates experiences of multiple environmental hazards and posture-related risks. The detailed items are listed in Eurofound (2012). Earnings are measured as monthly income, and are PPP-adjusted and denominated in euros. It is winsorised at the 1 and 99 percentiles to minimise the role of outliers. All other job quality indices are reported on a scale of 0 to 100, where 0 means poorest job quality and 100 means best job quality, except for *work intensity*, whereby the interpretation is the reverse (0=low intensity, 100=high intensity). For all job quality indices, except *prospects* and *social environment*, we use the SLIM versions of the indices, which are comparable across time. There are no SLIM indices for the job prospects and good social environment outcomes and analyses using these variables are only for year 2015.

Table A1 presents job quality means, by country and year, for all indices.

c) Additional variables

We source additional control variables at the individual level from the European Working Conditions survey. These measures include: age group (ages 15-35 (reference category), ages 36-45, ages 45-60, over 60, or missing), gender (male, female, or missing), country-based quartiles of typical weekly hours of work, education (pre-primary and primary (reference category), secondary, tertiary, or missing), occupation (managers (reference category), professionals; technicians and associate professionals; clerical support workers; services and sales workers; skilled agricultural/forestry/fishery workers; craft and related trades workers, plant and machine operators, and assemblers; elementary occupations; and missing). an indicator for company size above 250 workers (yes, no or missing), and sector (Agriculture, hunting, forestry and fishing (reference category)). For all categorical variables, we create an additional 'missing information' indicator, so that we avoid dropping observations with missing information. This additional category has no interpretational value, but only serves to preserve the number of observations.

Finally, we also include and the inverse hyperbolic sine transformation of changes in ICT capital (per 10,000 workers) as an additional control variable.

2. First-stage instrumental variable estimates

Table A2 presents the first-stage regression of the instrumental variable estimates shown in the paper (Table 2 Panel B).

Table A1: Job quality, by country and year

	Monthly income		Skills & discretion		Physical environment		Intensity		Working time quality		Social environment	Prospects
	2010	2015	2010	2015	2010	2015	2010	2015	2010	2015	2015	2015
Belgium	1644.399	1707.188	68.216	71.546	81.371	82.307	40.694	42.553	89.228	89.384	78.757	66.795
Bulgaria	557.766	744.869	49.577	51.600	77.010	79.541	34.428	38.646	80.940	82.767	87.110	62.554
Czech Republic	1034.974	1133.890	66.198	66.134	79.041	82.439	48.053	39.988	83.465	84.209	80.636	63.839
Germany	1669.705	1898.655	64.761	63.948	79.758	81.272	47.472	44.472	89.415	89.816	76.027	68.183
Estonia	840.646	1068.550	69.968	72.194	77.306	78.170	44.515	39.858	89.961	87.311	74.955	66.262
Spain	1563.554	1413.847	58.685	64.964	77.504	75.572	38.400	47.372	89.449	84.249	86.236	55.929
Finland	1897.655	1864.630	78.524	77.324	78.407	79.409	46.770	41.762	88.454	87.464	78.404	65.708
France	1643.454	1772.511	62.274	68.772	75.835	73.369	46.217	43.840	89.197	88.326	73.581	64.577
Greece	1214.856	1030.395	56.176	58.350	69.589	75.619	52.777	50.865	70.675	72.862	84.603	51.007
Hungary	680.507	797.537	59.159	55.653	71.912	79.344	53.983	51.210	84.572	83.953	83.799	63.796
Italy	1388.799	1358.383	61.225	62.593	79.270	82.041	42.923	40.701	88.685	88.431	74.602	54.681
Lithuania	713.454	1249.857	61.320	63.150	78.760	77.988	33.691	40.740	88.161	88.421	79.024	61.488
Latvia	590.256	755.092	63.317	53.524	78.633	79.319	34.072	31.528	83.748	85.575	76.596	62.467
Netherlands	1773.054	1780.445	73.839	76.600	83.649	83.689	37.867	37.724	87.817	88.397	75.254	63.959
Poland	875.041	1005.462	63.299	62.641	78.641	77.431	33.223	37.465	72.534	78.492	76.439	58.765
Portugal	921.110	924.266	57.700	56.646	78.954	83.298	33.765	34.374	87.029	88.564	85.567	56.403
Romania	497.286	622.002	56.962	60.138	78.630	73.102	43.334	59.207	69.324	78.605	80.651	66.960
Sweden	1557.973	1870.542	74.006	77.375	80.899	81.433	46.470	45.773	89.417	86.795	77.127	68.894
Slovakia	939.271	980.137	55.553	58.421	76.161	79.183	42.886	39.504	81.598	81.666	74.596	65.546
United Kingdom	1604.093	1900.859	68.761	73.991	81.545	82.511	45.595	43.865	85.501	82.030	80.346	68.454

Source: Bruegel based on European Working Conditions Surveys (2010, 2015)

Notes: The table reports the average values of various indices of job quality, weighted using the survey weight. The analysis sample is based on 20 European countries. No information is available for the prospects and social environment indices for 2010. Monthly income is PPP-adjusted and in euros, winsorised at the 1 and 99 percentiles to minimise the role of outliers. The rest of the job quality indices are measured on a scale of 0 to 100.

**Table A2: First stage IV results corresponding to Table 2
Panel B in main paper.**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Robotisation	Robotisation	Robotisation	Robotisation	Robotisation	Robotisation	Robotisation
Peer robot adoption	0.640*** (0.059)	0.628*** (0.059)	0.628*** (0.059)	0.628*** (0.059)	0.628*** (0.059)	0.624*** (0.107)	0.628*** (0.106)
1st stage F-stat	118.2	111.5	111.5	111.8	111.5	34.04	35.19
Number of observations	13,091	17,745	17,745	17,687	17,746	7,831	8,579

Source: Bruegel based on IFR, EUKLEMS, and European Working Conditions Surveys (2010, 2015)

Notes: The table reports the first stage regressions related to Panel B of Table 2. Robotisation is measured as the inverse hyperbolic sine transformation in the number of robots per 10,000 workers. All regressions include a constant and country and year fixed effects, and the following demographic and job controls: age group, gender, hours of work, education, occupation, company size, and the inverse hyperbolic sine transformation of changes in ICT capital. All regressions include two-way clustered standard errors at the country and industry levels. The instrumental variables based on the industry adoption of automation in all other countries in the sample (except that particular country). All regressions are weighted using the survey weight.

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



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