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Comparative report on the links between job quality, digitalisation, technology, and globalisation in Europe

Authors:

Laurène Thil & Mikkel Barslund (HIVA-KU Leuven)

Uyen Nguyen, Ludivine Martin & Laetitia Hauret (LISER)

Karol Madoń (IBS)

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Abstract

This report analyses the quality of employment in Europe in the current context of digital transformation and globalisation using data from the European Working Conditions Survey (EWCS) from 2005-2021. Job quality related to indicators for self-perceived fair pay, training, organisational support and being consulted at work has gone up. However, indicators for fair treatment at work and satisfaction with working time have deteriorated in the same period. Analysing the 2021 wave of the EWCS, we find a differentiated link between digitalisation, globalisation and job quality. Advanced digital technologies (ADT), automation risk, and exposure to artificial intelligence (AI) are associated with certain facets of job quality. The results suggest that ADT has a positive impact on certain job quality indicators (e.g. safety, fair pay, and autonomy), particularly for younger and older workers. However, automation may have negative causal effects on work-life balance, autonomy, and organisational support. The study suggests that exposure to AI increases the risk for medium-skilled workers. However, it also shows that AI is generally associated with higher levels of working time satisfaction, improved work-life balance, and better training opportunities. The impact of digital transformation on job quality varies across different socio-economic groups. Regarding offshoring, our results reveal both positive and negative effects on workers. On one hand, it can reduce poor safety and poor treatment at work and improve work-life balance. On the other hand, it is associated with working at a high-speed pace and can result in a reduction in training.

Keywords: digital transformation; globalisation; job quality

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1 Introduction

Creating high-quality jobs has become a crucial challenge for policymakers, labour unions, and companies in the digital age and globalisation. The European Commission High-Level Expert Group (2019) emphasised the need for addressing this challenge to ensure that employees are satisfied and happy in their jobs. For companies, it is recognised that happier employees tend to be more creative and productive (Huang *et al.*, 2016; Oswald *et al.*, 2015). Moreover, happier employees tend to take fewer absences from work (Nurski & Hoffmann, 2022). Overall, these factors positively contribute to better company performance (Wood *et al.*, 2012; Zelenski *et al.*, 2008).

However, the development of computers, other digital technologies and globalisation has significantly altered the organisational structures of companies, potentially influencing job quality. While digital technologies have undoubtedly brought about increased efficiency and innovation, there is a growing concern about their impact on the nature of jobs and tasks. Digitalisation and globalisation may lead to job displacement and shifts in skill requirements, potentially affecting the overall quality of jobs. It is crucial to understand the interplay between technological advancements job quality is for fostering a work environment that not only embraces innovation but also prioritises the well-being and satisfaction of employees.

Literature on the relationships between job quality and digitalisation and globalisation have concentrated mainly on specific dimensions of job quality,[1] falling to provide adequate exploration of other dimensions of job quality. Literature shows mixed results on the link between digitalisation and job quality (Martin & Hauret, 2022). Regarding globalisation, the existing evidence mainly relates to the offshorability of occupations (Blinder & Krueger, 2013). Except for a few papers such as Schmidpeter & Winter Ebmer (2018), previous research has tended to examine digitalisation and globalisation separately, overlooking the potential mutual influence of these changes on job quality.

In addition, the temporal evolution of job quality amid the ongoing development of digitalisation remains inadequately explored, particularly with regard to its nuanced dynamics across European countries. A more comprehensive and temporally nuanced examination is important to understand the multifaceted dimensions and evolving nature of job quality in the context of digitalisation across diverse European contexts. Finally, there is a notable lack in the current

[1] Labour income and work-life balance for digitalisation (Martin & Hauret (2022)) and wages and job security for globalisation (Hummels et al. (2018) and Crinò (2009))

body of research of a thorough investigation into the differentiated effects of technological change and globalisation on job quality, particularly with regard to employees' socio-economic characteristics such as gender, age, education, or occupations.

In this report, we will fill these gaps by investigating the job quality effects at the individual level of globalisation and three technological change indicators, namely advanced digital technologies, automation and artificial intelligence. Based on Warr (1999), Clark (2005) and UNECE (2015), this paper will focus on several facets of job quality: safety at work; fair treatment at work; satisfaction with working time, work-life balance; job insecurity; self-perceived fair pay; training, work high speed and autonomy. We will use data from the European Working Conditions Survey (EWCS), carried out by Eurofound in the years 2005, 2010, 2015, and 2021. The survey aims to offer a comprehensive perspective on the quality of work and employment across Europe (Eurofound, 2021). The methodology employed in this study involves descriptive and econometric analysis. To account for unobservable factors that may impact the adoption of digitalisation in certain occupations or sectors and subsequently affect job quality, an instrumental variable strategy will be used when feasible.

Our report indicates that, between 2005 and 2020, five out of the eight facets of job quality studied have improved in Europe. However, the feeling of fair treatment and satisfaction with working hours have deteriorated over this period. We show that advanced digital technologies (ADT) can enhance job quality for both younger and older workers by improving safety, ensuring fair pay, and increasing autonomy. On the other hand, automation can have a negative impact on work-life balance, autonomy, and organisational support. Medium-skilled workers are at a higher risk of negative effects from AI exposure, but AI is also associated with higher satisfaction, improved work-life balance, and better training opportunities, despite a faster work pace. This report emphasises the diverse impact of digital transformation on job quality among socio-economic groups, requiring specific strategies to tackle potential drawbacks, and highlights the subtle effects of this transformation. Regarding offshoring, the results underline that exposure to offshoring is positively associated to safety at work, fair treatment and work-life balance but negatively associated to training.

This report is structured as follows. In a first section, we will provide an overview of the existing literature grounded on the links between digitalisation, globalisation and job quality. Second, we will present the data and the methodologies. Third, we will describe the evolution of the eight dimension of job quality over the period 2005 to 2021 paying attention to the potential differences across some sociodemographic variables (gender, age and education level), occupations, sectors and countries. Fourth, we will present the results of the empirical analysis conducted on 2021 data and dedicated to the link between digitalisation, globalisation with the different dimensions of job quality. Fifth, the report concludes.

2 Related literature

2.1 Job quality and digitalisation and technology

Martin & Hauret (2022) recent literature review offers valuable insights into the relationship between digitalisation and six out of the eight job quality dimensions. They point out that previous empirical evidence has examined the relationship between digitalisation and job quality, primarily with respect to income from employment and working time and work-life balance. Nevertheless, regarding income from employment (mainly wage), there remains a lack of consensus on the effect of digitalisation on it. Some empirical evidence indeed indicate that routine manual tasks tend to be associated with lower wages (Autor & Handel, 2013; De La Rica *et al.*, 2020; Goos *et al.*, 2021) and induce wage polarisation (Autor & Dorn, 2013). Some others underline that digital skills are highly rewarded (Falck *et al.*, 2021), and that Artificial Intelligence appears to be more beneficial to workers' wages in the services sector than in manufacturing (Genz *et al.*, 2021).

Regarding working time and work-life balance measures, it appears that digital technologies blur the boundaries between work and personal life, resulting in detrimental effects on employees' work-life balance (Currie & Eveline, 2011) and an increase in work-life conflict (Wright *et al.*, 2014). Some studies proposed boundary management strategies to mitigate these negative links, including the use of integration versus segmentation techniques depending on temporal, psychological, or spatial dimensions (e.g., Derks *et al.* 2016; Sayah 2013).

However, analyses of the link between digitalisation and the others facets of job quality remain scarce and call for further research as the one we propose in this research report.

The existing research on the links between digitalisation and safety at work talk about the physical environment (no hard work), low injuries, and low physical health risk and has yielded inconclusive results. One the one hand, most of the evidence relates to the impact of robots and some report no link with physical environment (Anton *et al.*, 2020) while some report that robots can improve the physical environment by reducing injuries and the prevalence of poor health (Gunadi & Ryu, 2021). On the other hand, when it comes to the extended use of electronic devices or communication tools after work hours, there is evidence to suggest that they can contribute to the development of musculoskeletal disorders (Arlinghaus & Nachreiner, 2013; So *et al.*, 2017).

The evidence on the relationship between digitalisation and fair treatment is mainly focused on pay gap. Regarding gender pay gap, research shows mixed evidence on how digital transformation affects it. Robots increase the gap in Europe (Aksoy *et al.* 2020) but reduce it in the US (Ge and Zhou 2020). AI do not have an impact (at least in France) (Domini *et al.*, 2020). Germany observes a small reduction in the gender pay gap when task content is controlled, while no change is seen in Portugal or the US (Cortes *et al.* 2020). Recent studies performed in the framework of this research project, reveal that, on data from 37 countries, women earn 18.2% less than men, after accounting for differences in age, education level and skills. Moreover, there is a larger wage gap between routine and non-routine occupations for women compared to men. Capello *et al.* (2023) conducted a study that highlights the contribution of the digital service economy to the widening of intraregional wage inequalities in Europe. In discussing wage inequality not related to gender, Hudomiet and Willis (2021) found an age pay gap related to computer use. Edin *et al.* (2021) showed that occupational decline due to digital progress reduces cumulative earnings, particularly for lower-paid workers. Robots' positive effects on labour income appear for some groups of workers like high-skilled (Graetz & Michaels, 2018), or workers of the service sector (Dauth *et al.*, 2021).

When it comes to security of employment, research on previous waves of digital transformation suggests that there is a positive correlation between digitalisation and perceived job insecurity (e.g., Gallie *et al.* 2017; McGuinness *et al.* 2021). However, the relationship between the most recent technologies such as AI or robots and job security is more complex and nuanced, and the results are not always conclusive (Brougham & Haar, 2018; Lingmont & Alexiou, 2020). Similarly, career paths and professional stability have also been studied, but there is no clear consensus on the link between digitalisation and career development or stability (Genz *et al.*, 2021; or Bachmann *et al.*, 2021 from the Untangled project).

Regarding the link of digitalisation with social dialogue, some qualitative case studies exist and focus on the role of trade unions on digitalisation and a few on the other way around. For the latter, the main result is that digital transformation may have the tendency to weaken trade unions because of social media but some concrete examples mainly found in the gig economy literature highlight the importance of union (Eisele & Schneider, 2020; Wood & Lehdonvirta, 2021).

Most of the existing studies on the impact of digitalisation on skills development suggest that it changes the nature of job content (e.g., Atalay *et al.* 2018; Falck *et al.* 2021; Goos *et al.* 2021). Specifically, there is a decrease in demand for routine tasks, and an increase in demand for more abstract tasks, which require upskilling of incumbent workers. This shift towards more complex tasks can result in an overall positive impact on the development of higher-level skills among workers digitalisation (information technology in Bartel *et al.* 2007; robots in Dauth *et al.* 2021).

When it comes to employment-related relationships and work motivation, the use of technology has once again mixed effects. On the first sub-dimension, technology can strengthen formal relationships between co-workers by enhancing social support (Martin & Omrani, 2015, on computer use; Castellacci & Viñas-Bardolet, 2019, on Internet-based communication platforms). Nevertheless, it can be detrimental to informal relationships, leading to social isolation and tensions between colleagues (Askenazy & Caroli, 2010; Siampou *et al.* 2014; Melzer & Diewald, 2020). On the second sub-dimension of motivation and related outcomes such as job autonomy and decision making, research distinguishes between two types of technologies, which have opposite effects. Information technologies tend to decentralise decision making, giving more autonomy to employees, which can increase motivation. However, communication technologies tend to centralise decision making, reducing workers' autonomy, which can be demotivating (Bloom *et al.*, 2014; Cirillo *et al.*, 2021; Martin, 2017; 2020).

As for more recent technologies, there is no clear consensus yet on their impact on employment-related relationships or work motivation.

Some recent studies look at a broader range of job quality or working conditions. Flèche *et al.* (2023) use a French-specific variant of the European working conditions survey, with a 2013-2019 panel scale that included digitalisation measurements based on daily hours spent using desktops, laptops, emails, internet, or intranet. Their study covered ten non-monetary job quality factors: learning, autonomy, support, stability, development (training), physical integrity (risks), psychological integrity (stress), scheduling, flexibility and unconstrained work pace (work intensity). They highlight the polarisation of working conditions across different occupations. There is a positive correlation between increased digital usage and learning, physical risks, stress, and work intensity, while there is a negative correlation with development and scheduling.

Grimm (2023) focuses on Germany, utilising the Linked Personnel Panel (LPP) data from IAB between the years 2012 and 2018. He includes external measures of digital transformation such as routine task intensity from Mihaylof and Tijdens (2019), computer substitution risk from

Dengler and Matthes (2018), and AI exposure from Brynjolfsson *et al.* (2018) and Felten *et al.* (2018) and construct a working condition index. He discloses that basic digital use has a negative correlation with the working condition index, whereas advanced digital use has a positive correlation with the working condition index.

The differences in results found in the various analyses can be explained by differences in technologies and outcome studied, but also depend on the national and period context and employees' characteristics studied. There is here a clear need for future research to consider the influence of the research contexts on the existing results. One such context may take the form of the post pandemic hybrid work environment (Aksoy *et al.*, 2022).

2.2 Globalisation and job quality

The main dimension of globalisation studied in the literature are the offshorability index of occupations which involves the delegation of work to foreign firms (Blinder & Krueger, 2013). The studies on this phenomenon are quite older compared to those on digitalisation. While the issue of offshorability has received relatively less attention in the literature compared to digitalisation, some papers anticipate a rising risk of offshorability (Antràs *et al.*, 2006; Levy & Murnane, 2004). Levine (2005) focuses on offshore outsourcing, which involves the delegation of service sector jobs of white-collar workers to foreign firms. While offshore outsourcing has been cited as a contributing factor to the job losses following the 2001 recession, reports suggest that it may have only accounted for up to 10% of the cutbacks. Furthermore, it appears that in a single year, the number of jobs outsourced offshore was responsible for only 2% of the total employment in the United States. Also on US, Harrison and Mcmillan (2011) reveal that for firms that do significantly different tasks at home and abroad, foreign and domestic employment are complements.

Existing evidence related to job quality focus mainly on two dimensions of job quality, that are wages and job security (see the literature review by Hummels *et al.*, 2018 and Crinò, 2009).

Görg and Görlich (2015) examine the effects of offshoring on wages and job security as measured by unemployment probabilities among workers in Germany. Their research underlines that with an increase in materials offshoring, temporary workers experienced a notable decrease in wages, while permanent workers saw no impact on their wages or possibly even a rise. Also on Germany, Baumgarten *et al.* (2013) emphasise a significant and negative impact of offshoring on wages. Their research shows that the magnitude of this effect varies considerably depending on the task profile of workers' occupations. Hummels *et al.* (2014), on Danish data, show that within job spells, offshoring increases (decreases) the high-skilled (low-skilled) wage.

Few studies existing on the other dimensions of job quality. For instance, Crinò (2012) investigates the impact of material offshoring and service offshoring on skill demand at the occupation level in Western Europe, specifically in relation to the skills development dimension of job quality. The study highlights that while material offshoring results in the substitution of low-skilled labour, service offshoring leads to an increase in the relative demand for high- and medium-skilled workers.

2.3 Digitalisation, globalisation and job quality

Recent analyses at the EU level examine the impact of digital transformation in conjunction with the global value chain (GVC) on different aspects of job quality. For instance, Parteka *et al.* (2023) and Nikulin *et al.* (2022), using the European working condition survey of 2015, study the relations between digital transformation and GVC on six aspects of job quality: social environment, skills and discretion, physical environment, prospects, working time quality, and work intensity. The study findings indicate that different level of software, robot and AI exposure measured using patent data from Webb (2020) suggest comparable connections between different levels of exposure to software and robots but dissimilar links with AI. For instance, according to Nikulin *et al.* (2022), jobs with high software and robot exposure tend to have lower quality as GVC involvement increases. Different finding are revealed for jobs with AI exposure, while a greater exposure is linked to a better social environment, which is further enhanced by GVC. There were no substantial variations detected across different levels of AI exposure concerning skill and discretion, and prospects. GVC exhibited stability in skill and discretion but exhibited a decrease in prospects. Low AI exposure showed that physical environment and working time quality are superior. A relationship that remained stable with GVC for physical environment while slightly increasing for working time quality. However, work intensity is greater with high exposure to AI but decreases with GVC to the point of being no different from other levels of intensity when GVC is medium and high.

There also exist some studies, such as the one conducted by Schmidpeter and Winter-Ebmer (2018) that investigate the impact of automation and offshorability (Blinder & Krueger, 2013 index) on wages, re-employability and employment stability. Their findings suggest that the presence of routine tasks and offshoring negatively affects re-employment opportunities. For those who are successfully re-employed, the study indicates that offshorability (but not automation) has a positive effect on job duration and wages.

2.4 Heterogeneity of links between digitalisation, globalisation and job quality

The heterogeneity of links between digitalisation, and/or globalisation with the different job quality dimensions or a job quality index due to various socio-economic, occupational, business sectoral factors is scarcely explored. Nevertheless, Eurofound (2021) highlights that discrepancies arise concerning job quality between countries, occupations, gender, or age, even without explicitly examining the role of digital transformation or globalisation.

Grimm (2023) studying digital transformation and a job quality index in the German context shows that gender, age, and business sector present distinct findings from the average. Martin *et al.* (2022) demonstrate differences based on gender and management positions regarding the relationship between the use of technology outside working hours and workers' work-life balance promoting employee well-being, satisfaction, and overall quality of life.

3 Data and methodologies

3.1 Data

3.1.1 Job quality

In order to analyse the various dimensions of job quality, we use data from the European Working Conditions Survey (EWCS) conducted by Eurofound in 2005, 2010, 2015, and 2021. The survey's objective is to provide a comprehensive view of the quality of work and employment in Europe (Eurofound, 2021). Themes covered include employment status, working time duration and organisation, work organisation, learning and training, physical and psychosocial risk factors, health and safety, work-life balance, worker participation, earnings and financial security, as well as work and health.

Based on this data, we examine eight dimensions of job quality for employees (self-employed workers are not included in our study): (1) safety at work, (2) fair treatment, (3) working time and work life balance, (4) security of employment, (5) self-perceived fair pays, (6) social dialogue, (7) training paid by employer, (8) employment related relationships and work motivation. To capture these dimensions, we constructed several indicators, which are briefly described below. Annex 1 presents them more in details.

To measure **safety at work**, we compute the number of risks that employees are exposed to at work among nine potential risks which covers ergonomic (tiring/painful positions, lifting/moving people, carrying/moving heavy loads), environmental (exposition to noise, chemical products, materials which can be infectious) and physical risks (backache, muscular pains). In the econometric section, we dichotomise this indicator. It takes the value 1 if the number of risks employees perceive is larger than the mean number of risks in their occupation and 0 otherwise.

To investigate **fair treatment** in the workplace, we developed an indicator that assigns a value of 1 if an employee experiences any of the following three forms of asocial behaviour: verbal abuse, unwanted sexual attention, or physical violence, 0 otherwise.

To study **working time and work life balance**, we use three main indicators. First, the satisfaction with working time which is equal to 1 when the absolute difference between the preferred working hours per week and the effective working hours per week is lower than the average difference. Second, the fact to work at very high speed, which is equal to 1 if the employee indicating working at a very high speed. Third, the level of work-balance. It is assessed on a scale of 1 to 4, where 1 indicates that working hours are not compatible with social or family commitments outside of work, and 4 indicates a high level of compatibility. In the econometric part, we dichotomise this indicator; it is equal to 1 if the value is at least 3.

To study **security of employment**, we use an indicator equals to 1 if a respondent reports the possibility of losing his job within the next six months, 0 otherwise.

To study **self-perceived fair pay**, we rely on an indicator equals to 1 if respondents feel they are being adequately compensated for their efforts and achievements in their job, 0 otherwise.

To reflect **social dialogue**, we compute an indicator equal to 1 if in the respondent's company at least one of these types of social dialogue exists: representation by trade union, works council, or similar employee committee; a health and safety delegate or committee, regular meetings where employees can express their views about the organisation. Note that this indicator is available only from 2015 and 2021.

For **training** dimension, we use an indicator equal to one if respondents reported receiving training (on the job or paid by the employer), 0 otherwise.

Employment related relationships and work motivation. We compute two indicators on employment related relationships. The first one equal to 1 if respondents are supported at work at least by their colleagues or their manager, 0 otherwise. The second equals to 1 if respondents are consulted before objectives are set for their work or are involved in improving the work organisation or work processes of their department or organisation. Unfortunately, the data we are working with does not include any direct measures of work motivation. However, the existing literature suggests that autonomy is a critical factor that can positively impact motivation. Therefore, in the absence of direct measures, we use autonomy as a proxy for work motivation in our analysis. However, we acknowledge that this approach may not capture all aspects of work motivation. The autonomy at work dimension is captured through three questions related to different types of autonomy: (1) autonomy in the order of tasks, (2) autonomy in choosing the methods of work, and (3) autonomy in determining the speed of work. The indicator reflects whether the respondent reports having at least one type of autonomy at work.

3.1.2 Data on digital transformation and globalisation

To examine the correlation and the causal relationship between megatrends, such as digital transformation and globalisation, and various aspects of job quality, we analysed the most recent EWCS survey. We utilised external data to gauge the extent of digital transformation and globalisation, which are presented below.

Digital transformation

The concept of digital transformation is broad. The digital transformation of work refers to the integration and adoption of digital technologies, tools, and processes within the workplace to enhance productivity, efficiency, and collaboration. It involves the transformation of traditional manual or analogue tasks and processes into digital formats, enabling automation, data-driven decision making, and the use of advanced technologies like artificial intelligence, machine learning, cloud computing, and robotics.

To address digital transformation, we are concentrating on advanced digital technologies, including artificial intelligence and automation.

Artificial intelligence

To measure AI, we used data from the paper of Tolan *et al.* (2020). The explicit focus on AI distinguishes this analysis from studies on robotisation (Acemoglu and Restrepo, 2018), digitalisation and online platforms (Agrawal *et al.*, 2015), and the general occupational impact of technological progress and automation (Autor, 2015). That is, automation through technologies that do not require AI, e.g., self-checkout machines that replace human cashiers in supermarkets, is not considered in this framework.

These AI-related metrics reflect the intensity of current research and development in different AI techniques. The authors acknowledge that the 'research intensity' indicator is not necessarily a good proxy of future AI progress, since breakthroughs do not always appear where more research effort is spent, and there may be dead ends that are not obvious yet. But future AI progress is hardly difficult to predict and this indicator aims to identify which occupations and types of task contents are more directly related to pre-chatGPT developments in AI research. The present analysis is limited to the technical potential of AI (i.e., the things that AI could potentially do at work).

To analyse the links between AI and job quality dimensions, we matched this data to the individual EWCS data at the occupation level.

Automation

Arntz *et al.* (2017) used PIAAC detailed task data to take into account the spectrum of tasks within occupations. Their measure of automation potential is thus assessed at the occupational level, while including the job-level variation in automation exposure derived from the PIAAC data. They also used an imputation method to derive a weighted occupational risk of automation that varies across individuals according to their characteristics. We matched this data to the individual EWCS data at the occupation level.

Globalisation

The offshorability of an occupation refers to the degree to which the tasks and responsibilities associated with that occupation can be effectively carried out or relocated to another country, typically through outsourcing or remote work arrangements. It indicates the extent to which the work can be performed by individuals in a different geographic location, often with the use of technology and communication tools.

The offshorability index measures the ease with which an occupation can be offshored to a different country. In order to distinguish between offshorable and non-offshorable occupations, we use the latest available measures from Blinder and Krueger (2013) classification based on professional coders' assessments in the PDII US survey. Occupations are classified as offshorable according to the PDII are 'offshorable, though with some difficulties or loss of quality that can be overcome' (offshorability score 4 out of 5) or that are 'easily offshorable with only minor or no difficulties or loss of quality' (offshorability score 5 out of 5). They are adapted to ISCO codes by Lewandowski *et al.* (2022) using official ILO crosswalk to map the SOC codes (used in PDII) into ISCO codes.

3.2 Methodologies

During the initial stage (Section 4), we use descriptive statistics to analyse changes in the dimensions of job quality for European employees between 2005 and 2021. We also examine this evolution with respect to various sociodemographic variables (including gender, age category, level of education), activity sector, and country group.

In a second stage (Section 5), we study, on the most recent wave of EWCS, the link between the various dimensions of job quality and digital transformation and globalisation. As the three digital transformation indicators come from three different sources and are significantly correlated, we decided not to introduce them simultaneously in the estimation models but rather separately.[2]

Given the binary nature of our dependent variables, we use Probit models to estimate job quality measures and report average marginal effects (AMEs). A concern with Probit models is that non-random variation in ADT, automation, and AI may not be readily interpreted as a causal effect. Unobservable factors that affect the adoption of digitalisation in occupations or sectors are likely to also affect job quality in those occupations or sectors. To address this issue, we will adopt an instrumental variable (IV) strategy. Unfortunately, due to a lack of valid instruments, we are unable to apply the IV strategy for ADT and AI. For automation risk, as a source of variation, we rely on the methodology introduced by Acemoglu and Restrepo (2020). Specifically, we use the average automation's exposure rate in occupations among six countries not considered in our study, namely Austria, Canada, Estonia, Finland, Norway, and the United Kingdom.

It should be noted that the samples used for the various Probit models varies for two reasons. Firstly, the EWCS survey was conducted on a module-by-module basis, meaning that participants were not questioned on all modules. Secondly, some indicators used to study the link between megatrends and job quality are unavailable for certain occupations, sectors or countries. The final sample covers 12 countries: Belgium, Czech Rep, Denmark, Germany, Spain, France, Ireland, Italy, Netherlands, Poland, Slovakia, Sweden

[2] Correlation between AI and automation: -0.76, between AI and ADT : 0.31, between ADT and automation -0.269. These correlations are significant at the 10% threshold.

4 Job quality in EU from 2005-2021

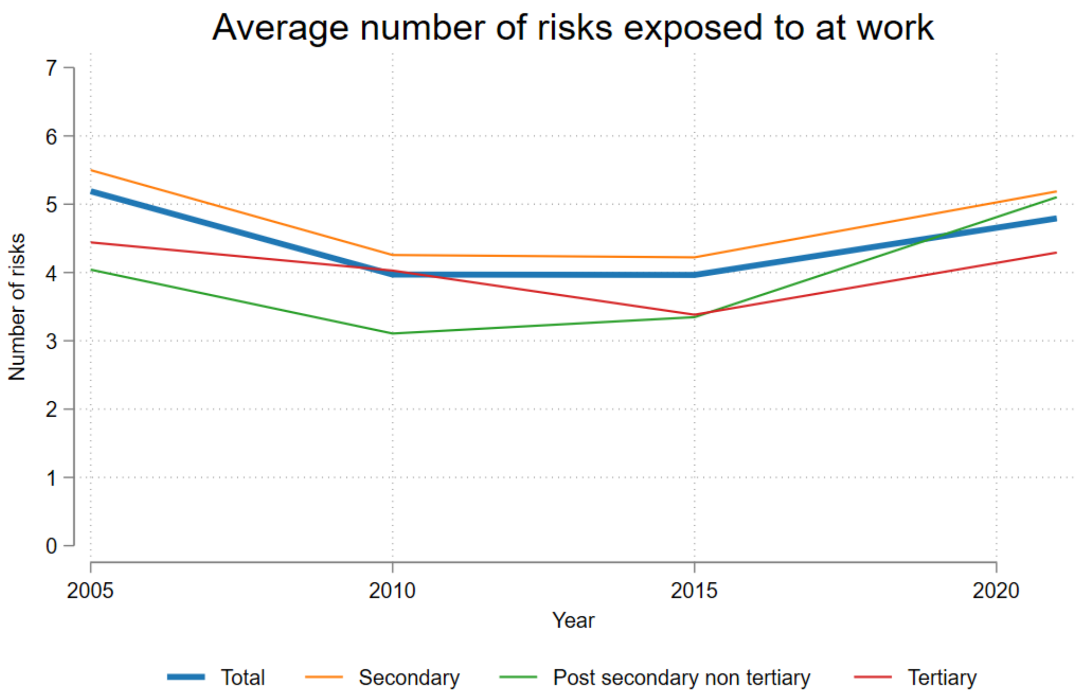
In this section we examine the evolution between 2005 and 2021 for the various job quality dimensions. We also give attention to the relevant differences across gender, age, education levels, occupations, sectors and country groups.[3]

4.1 Safety at work

The number of risks exposed to at work is on average between 4 and 5 (out of 9) in 2021 (Figure 1). The trend has been decreasing between 2005 and 2015 from 5 to 4 risks and is increasing between 2015 and 2021 (to 4.8). Around 75% of this increase is due to an increase in backache and muscular pain in shoulders, an increase in work done in tiring or painful position, and an increase in noise level. Some differences can be observed by education level, with the respondents with secondary education being exposed to more risks at work than respondents with post-secondary and tertiary education over time. On average, the different education level groups follow the same evolution, with the exception of post-secondary non tertiary level which increases more sharply than the two other levels (3 in 2010 to 5 in 2021). In 2021, respondents with tertiary education were exposed on average to 4.2 risks, compared to 5.1 risks for lower-educated respondents. The number of risks also differs according to different occupations; with skilled agricultural, forestry and fishery and craft workers being always exposed to more risks than other occupations, with an average of 6 risks in 2021 (see Annex 3 Figure a 1). Clerical support workers are exposed to fewer risks over time, from 3 risks in 2015 to 3.7 in 2021. Some sectors are also exposed to more risks than others (see Annex 3 Figure a 2). On average, those employed in other service reported fewer risks than those working in construction, transport, and storage, who reported being exposed to respectively approximately 4 and 5 risks in 2021. The number of risks faced by workers in public services and education saw a significant increase, rising from 3.9 in 2010 to 5.2 in 2021.

[3] This metric is binary, taking a value of 1 when the absolute difference between preferred weekly working hours and actual weekly working hours is 1.70 (the mean of the difference between the preferred working hours per week and the effective working hours per week between 2010 and 2021), and 0 otherwise.

Figure 1. Risks at work indicator

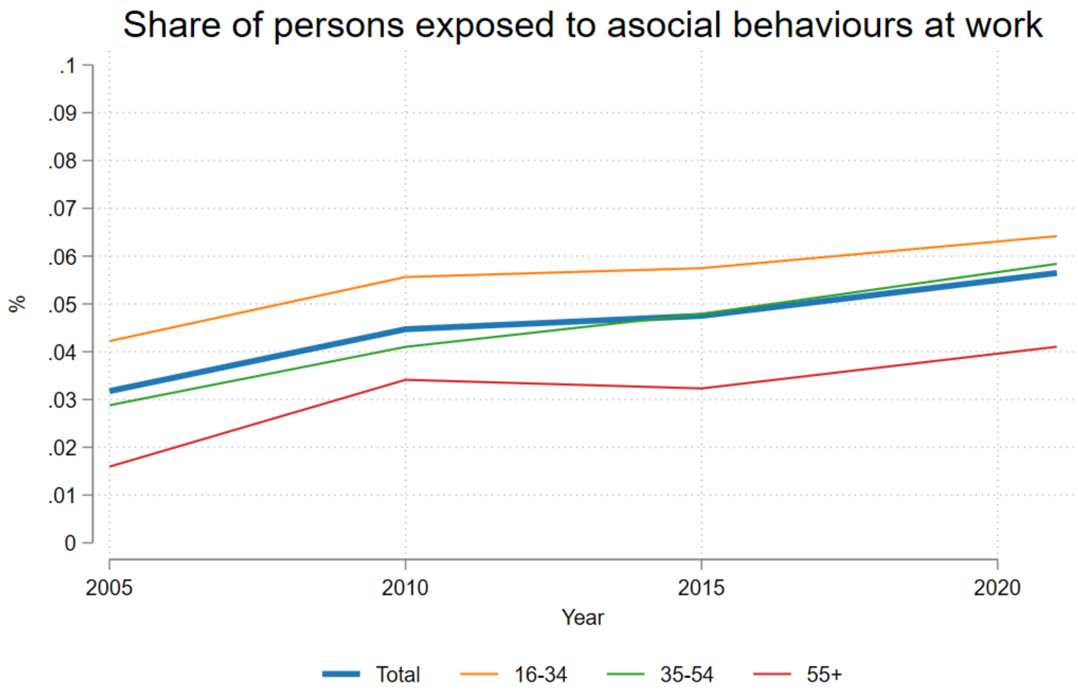


Note: Aggregated indicator based on Q30a, Q30b, Q30c, Q30e, Q29b, Q29g, Q29i, Q78c andQ78d, representing different types of risks at work. All the questions have been rescaled to binary indicators indicating if the person is exposed to the risk (0 No - 1 Yes). The average number of risks exposed to at work is the mean of the sum of these binary indicators. EWCS weighted data for all EU-27 countries.

4.2 Fair treatment

According to Figure 2, in 2021, about 6% of those surveyed reported experiencing different types of asocial behaviours, such as verbal abuse, unwanted sexual attention, and physical violence, at their workplace. Such exposure is a clear indication of unfair treatment in the workplace. Interestingly, the percentage of those reporting asocial behaviours has doubled from 2005 to 2021. Figure 2 also shows that younger workers are more likely to report such behaviours than older workers, with over 6% of those aged 16 to 34 reporting incidents compared to 4% of those aged 55 and above. In 2021, women were found to report incidents of asocial behaviours more frequently than men, with approximately 7% of women and 5% of men reporting such incidents. Furthermore, the gender gap in the reporting of asocial behaviours has increased over time (Annex 4 Figure a 3). In 2021, there is nearly no difference across education levels, but in 2015, workers with tertiary education reported less often asocial behaviours (Annex 4 Figure a 3).

Figure 2. Share of persons exposed to asocial behaviours



Note: Aggregated indicator based on Q80a, Q80b and Q81a, representing different types of asocial behaviour at work. All the questions have been rescaled to binary indicators indicating if the person is exposed to the asocial behaviour (0 No - 1 Yes). The share of persons exposed to at least one asocial behaviour at work is the share of observations for which the sum of these binary indicators is greater than 0. EWCS weighted data for all EU-27 countries.

The prevalence of such behaviours differs across sectors, with workers in agriculture and industry being exposed the least since 2005, while workers in public services and education are exposed the most, reaching between 8 and 9% in 2021 (Annex 4 Figure a 4).

There are some discrepancies among various occupations regarding the prevalence of asocial behaviours at work over time (Annex 4 Figure a 5). Service and sales workers, in particular, reported such incidents more frequently. Interestingly, skilled agricultural workers reported fewer incidents of asocial behaviours in 2015, with only 1% reporting such incidents. However, in 2021, the percentage increased to nearly 6%.

4.3 Working time and work life balance

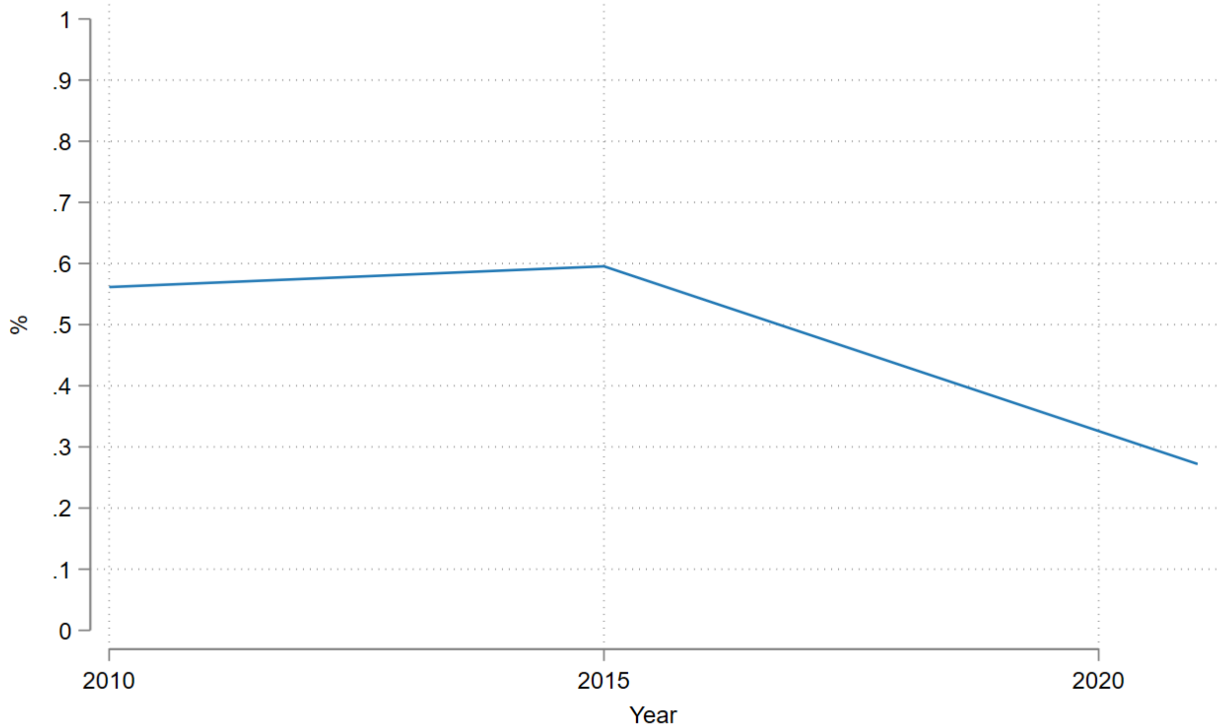
Working time satisfaction

In both 2010 and 2015, approximately 60% of respondents expressed satisfaction with their working hours (see Figure 3).[4] However, this percentage experiences a significant decline in 2021, dropping to less than 30%. This decline could be partially attributed to the widespread

[4] Mean of the difference between the preferred working hours per week and the effective working hours per week between 2010 and 2021.

adoption of teleworking during the COVID-19 pandemic. Nevertheless, no noteworthy variations were noted across various respondent groups and characteristics.

Figure 3. Share of persons satisfied with their working time

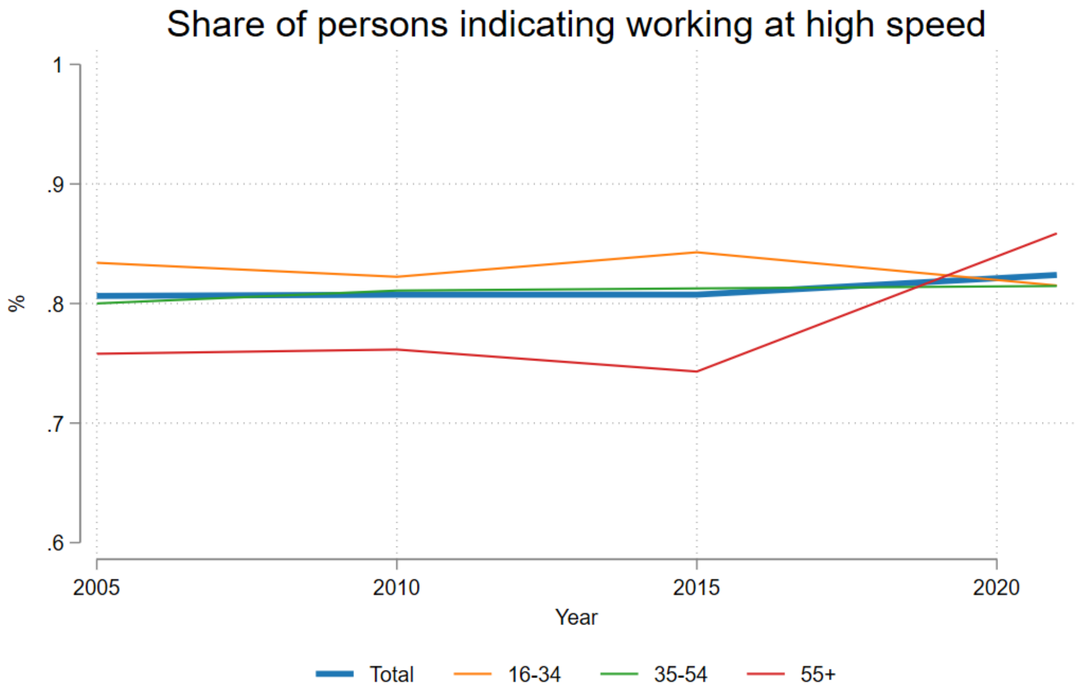


Note: Working time satisfaction is equal to 1 if the employee is satisfied with their working time, specifically when the absolute difference between the preferred working hours per week and the effective working hours per week is 1,7, 0 otherwise. EWCS weighted data for all EU-27 countries.

Working at a very high speed

According to Figure 4, approximately 80% of respondents reported working at a high speed since 2005. However, there are differences across age categories, with older workers (aged 55 and above) reporting more frequent high-speed work in 2021 (85%), whereas they used to report less frequent high-speed work than younger workers between 2005 and 2015. Country groups also exhibit some variations, with Nordic countries having more workers indicating high-speed work from 2005 to 2021, while fewer workers in eastern countries reported working at a high speed from 2005 to 2015. In 2021, however, these disparities across country groups have diminished (Annex5 Figure a 6).

Figure 4. Work at high speed



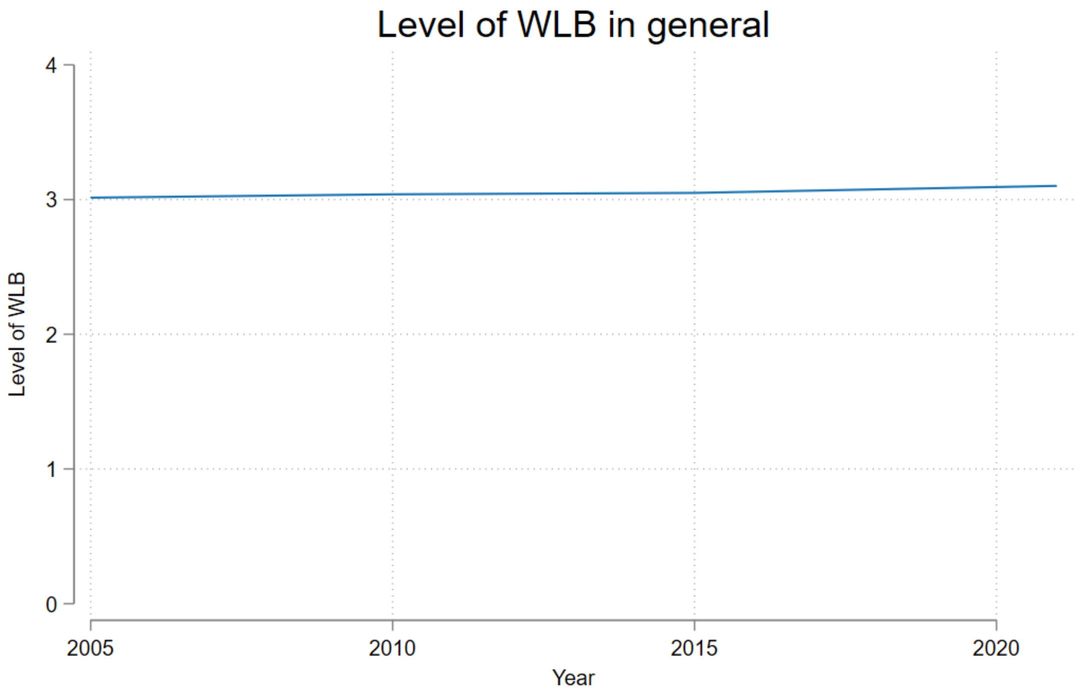
Note: Question 40a: Does your job involve working at a very high speed? Rescaled to a binary indicator indicating if the person is working at high speed (0 No - 1 Yes). EWCS weighted data for all EU-27 countries.

There are also disparities across occupations, with skilled agricultural, forestry, and fishery workers being the most exposed to high-speed work in 2021 while those in elementary occupations are the least exposed. Between 2015 and 2021, the percentage of skilled agricultural, forestry, and fishery workers who reported working at high speed increased significantly, rising from 75% to 88% (Annex 5 Figure a 7).

Work-life balance

The level of work-life balance is assessed on a scale of 1 to 4, where 1 indicates that working hours are not compatible with social or family commitments outside of work, and 4 indicates a high level of compatibility. From 2005 to 2021, the level of work-life balance remained stable at around 3. No relevant differences were observed across workers groups.

Figure 5. Level of work life balance in general

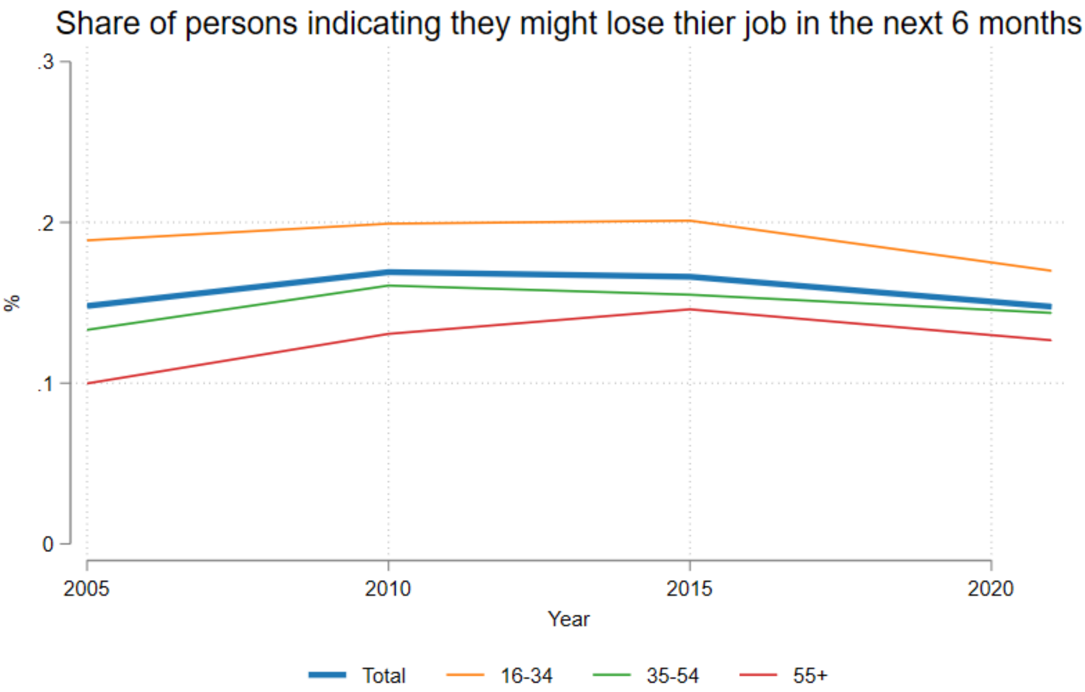


Note: Question 44 In general, how do your working hours fit in with your family or social commitments outside work? 1 Not at all well-4Very well. EWCS weighted data for all EU-27 countries.

4.4 Job insecurity

Between 2005 and 2021, the percentage of respondents who report the possibility of losing their job within the next six months has fluctuated between 15% and 16% (Figure 6). However, there are differences in job insecurity across age categories with younger workers being always more insecure about their job than older workers (Figure 6). There are differences across occupations, with the highest level of job insecurity in 2021 being reported by those workers in elementary occupations (22%) and the lowest by skilled agricultural workers (8%) (Annex 6 Figure a 8).

Figure 6 Job insecurity



Note: Question 89g: I might lose my job in the next 6 months (0 Strongly disagree, tend to disagree and neither agree nor disagree - 1 Tend to agree and strongly agree). EWCS weighted data for all EU-27 countries.

Similarly, job insecurity also varies across sectors, with workers in other services having the lowest level throughout the period (Annex 6 Figure a 9).

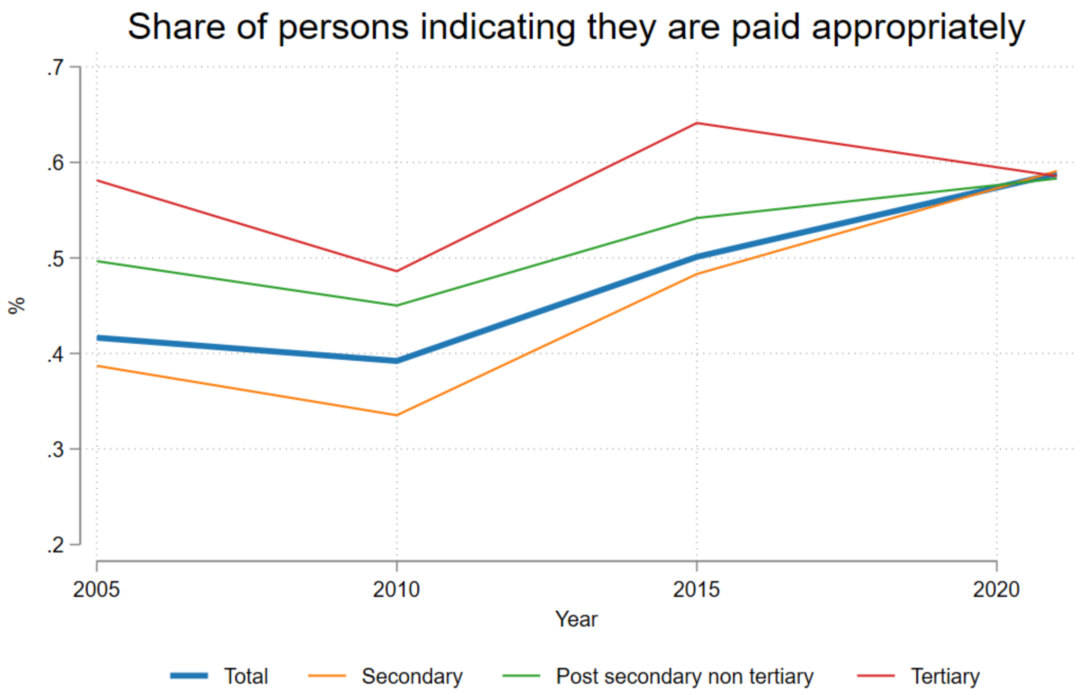
In 2021, western countries had the lowest proportion of respondents reporting job insecurity, while southern countries had the highest proportion. The percentage of respondents reporting job insecurity in southern countries increased the most between 2005 and 2015, rising from 13% to 22%, and remained high at 19% in 2021 (Annex 6 Figure a 10). Finally, job insecurity varies depending on the level of education. In 2005, 2010, and 2021, workers with higher education reported less job insecurity compared to those with lower education. However, there was an interesting shift in 2015 when workers with tertiary education reported the highest levels of job insecurity (Annex 6 Figure a 10).

4.5 Self-perceived fair pay

Over time, the proportion of respondents who feel they are being adequately compensated for their efforts and achievements in their job has risen from 41% in 2005 to 59% in 2021 (Figure 7). In 2021, there were no disparities in reported pay appropriateness across education levels. However, between 2005 and 2015, individuals with tertiary education consistently reported higher rates of pay appropriateness compared to those with lower levels of education.

Conversely, workers with secondary education reported less frequently that their pay was appropriate during this time period, as shown in Figure 7.

Figure 7. The feeling of being paid appropriately



Note: Question 89a: Considering all my efforts and achievements in my job, I feel I get paid appropriately (0 Strongly disagree, tend to disagree and neither agree nor disagree - 1 Tend to agree and strongly agree). EWCS weighted data for all EU-27 countries.

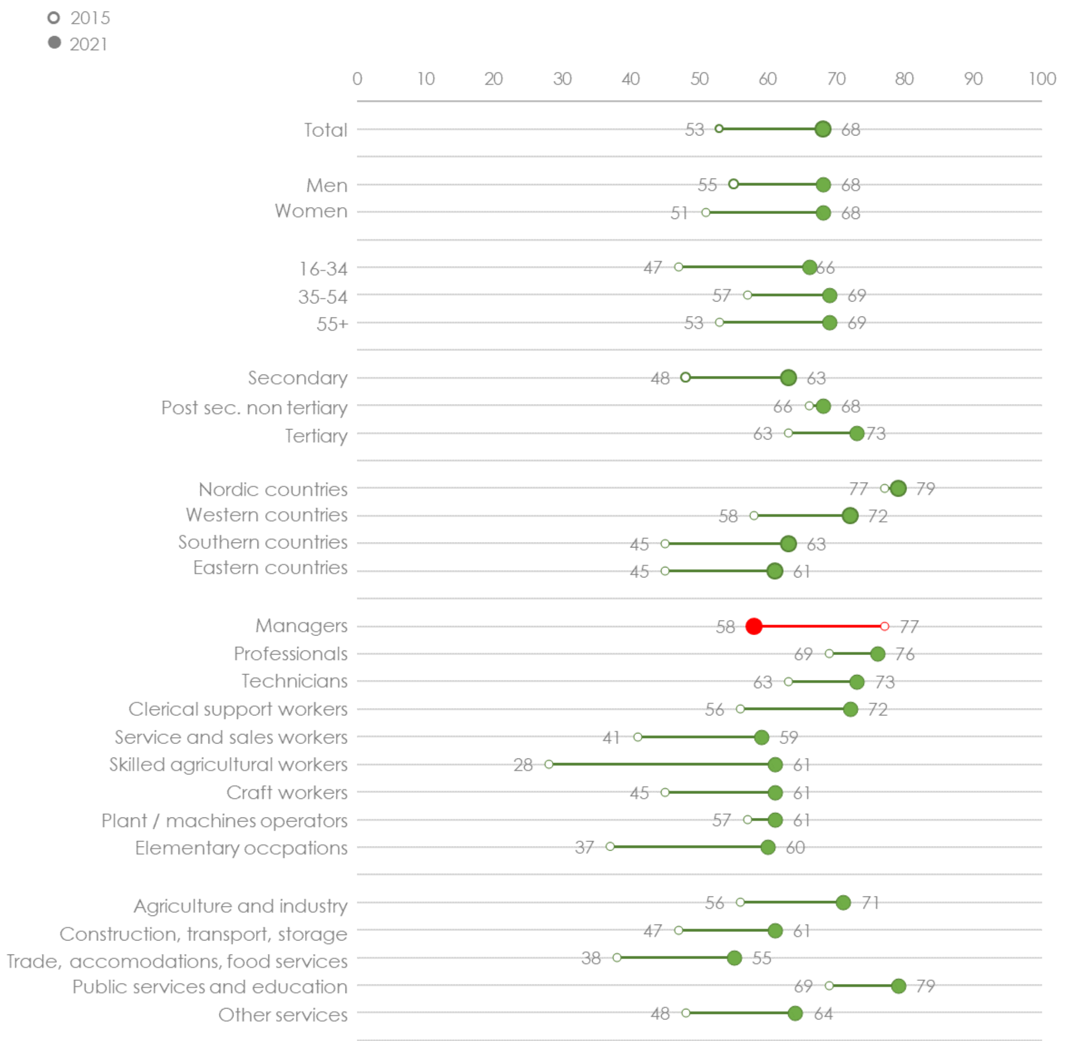
Women report systematically less often being paid appropriately than men, with 55% compared to 61% in 2021 (Annex 7 Figure a 11). There exist disparities among country groups regarding workers' perceptions of their pay. Since 2010, employees in Nordic countries have felt that their compensation is more adequate than that of workers in other countries, with a 64% satisfaction rate in 2021 compared to 55% in Southern countries (Annex 7 Figure a 12). This trend is relatively consistent across various sectors, with around 60% of workers feeling appropriately paid in 2021, except for those in public services and education, who had a 53% satisfaction rate in the same year (Annex 7 Figure a 12).

The perception of being paid appropriately is generally comparable across occupations, except for skilled agricultural workers who have consistently reported lower levels of satisfaction in 2005, 2010, and 2021, with only 46% indicating satisfaction in 2021 (Annex 7 Figure a 13).

4.6 Social dialogue

From 2015 to 2021, the percentage of respondents reporting having at least one form of social dialogue available in their firm increased from 53% to 68%. Furthermore, the share of respondents indicating social dialogue options is higher in Nordic countries and lower in Eastern countries. Also, fewer respondents with lower education levels reported having social dialogue options than those with higher education. In 2021, professional respondents had a greater percentage (76%) of reported social dialogue options than managers (58%). Additionally, managers were the only group whose proportion of respondents reporting at least one social dialogue option in their company decreased from 77% in 2015 to 58% in 2021 (Figure 8).

Figure 8. Share of persons having at least one social dialogue option available in the company

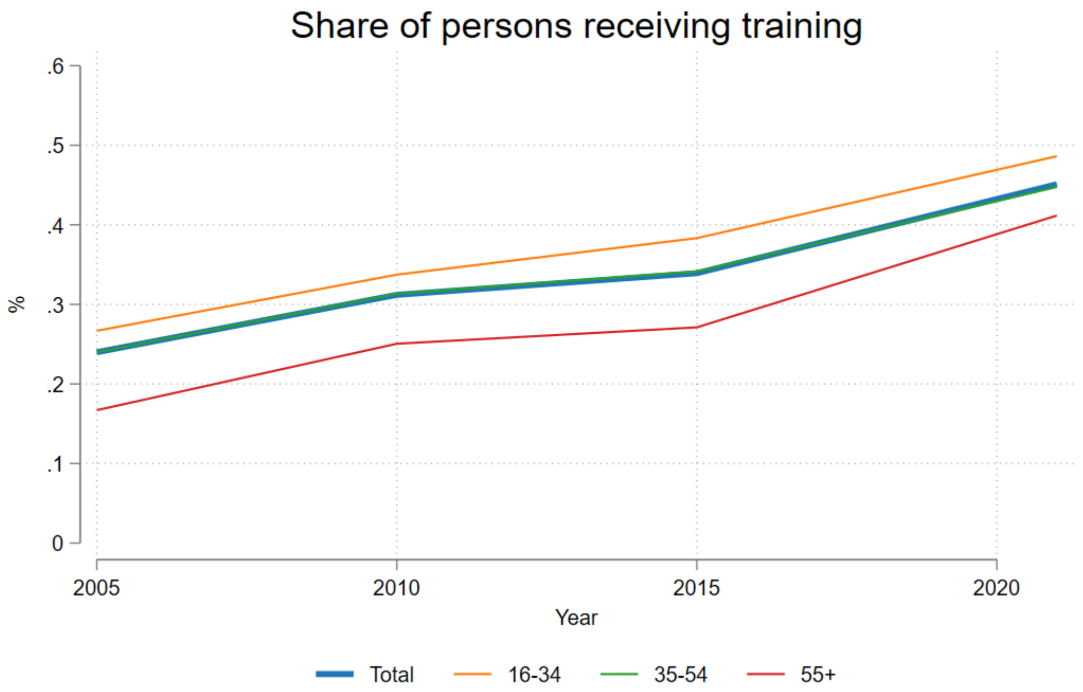


Note: Aggregated indicator based on Q71a, Q71b, Q71c, representing different options of social dialogue available in the company. All the questions have been rescaled to binary indicators indicating if the option is available in the company (0 No – 1 Yes). The share of persons having social dialogue options is the share of observations that have at least one social dialogue option in their company. EWCS weighted data for all EU-27 countries.

4.7 Training paid by employer

The percentage of respondents who reported receiving training (on the job or paid by the employer) increased from 25% in 2005 to 45% in 2021 (Figure 9). Figure 9 also illustrates that the number of older workers who have received training is lower compared to their younger counterparts, indicating that there are variations in training rates among different age groups.

Figure 9. Share of persons having undergone training



Note: Aggregated indicator based on Q65a, Q65c, representing different options of training (paid by the employer or on the job). These questions have been rescaled to binary indicators indicating if the person has undergone such training (0 No - 1 Yes). The share of persons having undergone training is the share of observations for which the sum of these binary indicators is greater than 0. EWCS weighted data for all EU-27 countries.

The share of persons receiving training is influenced by their educational attainment (Annex 8 Figure a 14). On average, workers with secondary education are 10 percentage points less likely to report having received training compared to those with higher levels of education. Regarding country groups, since 2005, Nordic countries have consistently had higher proportions of workers reporting receiving training, with rates around 50%. Conversely, in 2005, only 15% of workers in Southern countries reported having received training, while rates were 22% in Eastern countries and 38% in Western countries. However, the gap between these three groups and Nordic countries has gradually decreased since 2005. As of 2021, Western countries have caught up with Nordic countries, with training rates at 48%, followed by Eastern countries at 44%, and Southern countries with the lowest rates at 41% (Annex 8 Figure a 14).

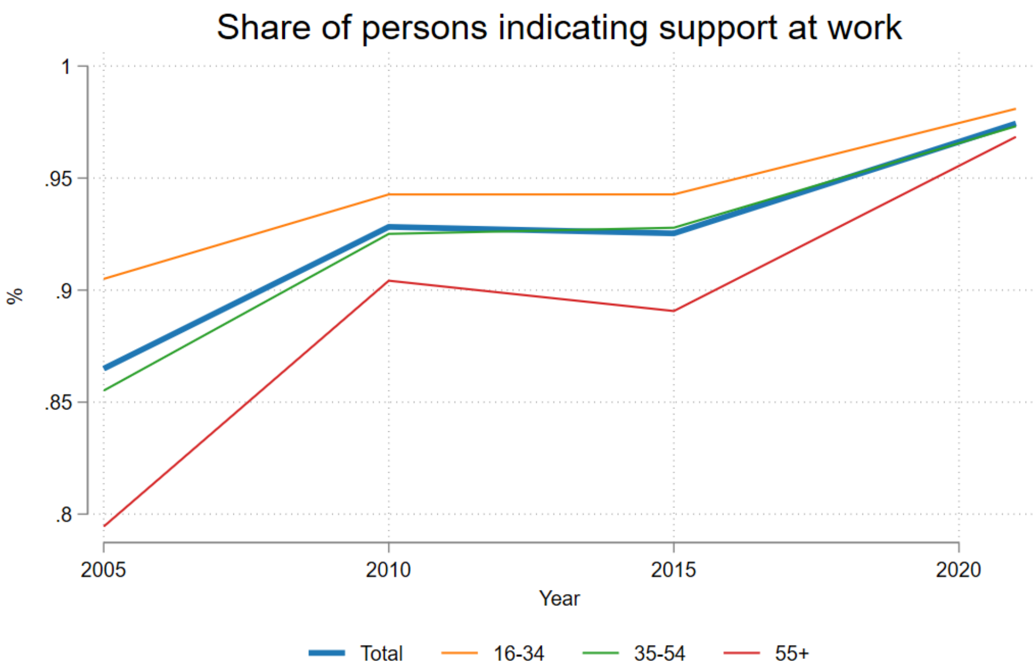
There are disparities in training rates among different occupations. In 2021, technicians and associate professionals had the highest training rate at 52%, while skilled agricultural workers had the lowest rate at 29%. All occupations generally follow a similar trend, except for managers who had a more significant increase in the share of individuals reporting training from 30% in 2015 to 49% in 2021 (Annex 8 Figure a 15). Moreover, there are variations in training rates across sectors, with a higher proportion of respondents working in public services and education (51%) indicating training receipt compared to those in trade, accommodation, and food services (40%) in 2021 (Annex 8 Figure a 16).

4.8 Employment-related relationships and work motivation

Organisational support

From 2005 to 2021, the proportion of individuals reporting support from their colleagues or supervisors in the workplace has consistently remained above 85% on average, with the most recent survey in 2021 indicating a nearly universal level of support at approximately 97% (Figure 10). In 2005, there was a wider discrepancy between age groups regarding support at work, with 91% of younger workers (16-34) indicating support compared to 79% of older workers (55+). However, as of 2021, the differences across age groups have nearly disappeared with all age groups being around 97% to 98% (Figure 10).

Figure 10. Organisational support



Note: Aggregated indicator based on Q61a and Q61b, representing different types of support at work (from the colleagues or the manager). All the questions have been rescaled to binary indicators indicating if the person receives such support (0 No - 1 Yes). The share of persons indicating they have support at work is the share of observations for which the sum of these binary indicators is greater than 0. EWCS weighted data for all EU-27 countries.

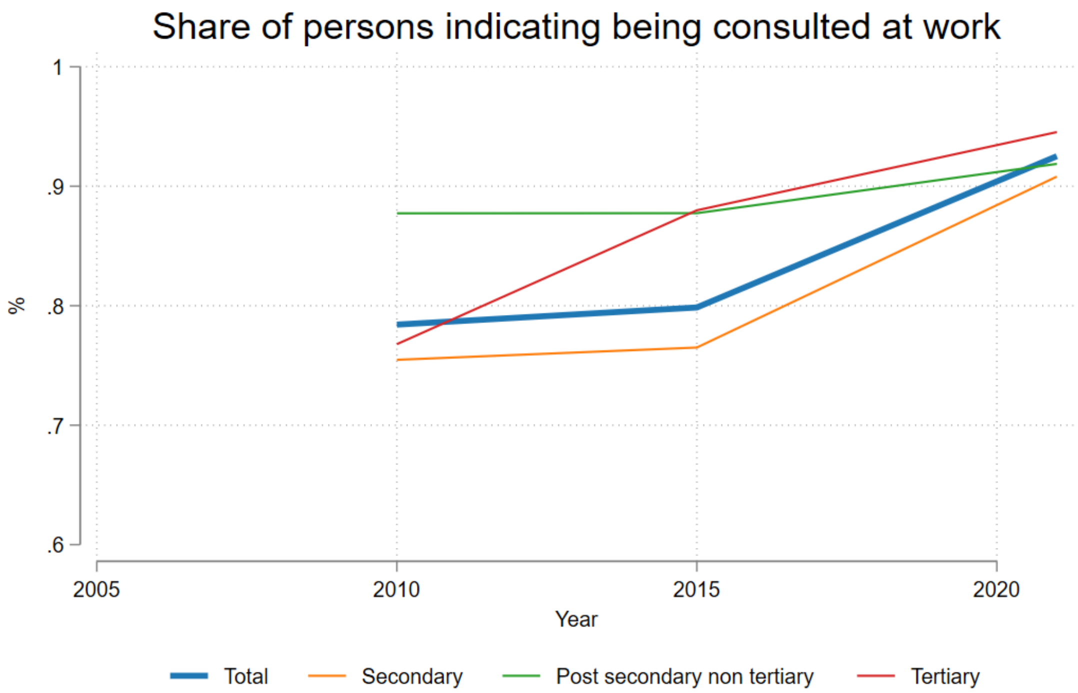
The share of persons reporting support at work is different according to their education level, with higher educated workers reporting more often support both in 2005 and 2021. However, there was a consistent trend from 2005-2010, where workers with a lower education level (secondary level) reported less often support compared to those with post-secondary non-tertiary education (Annex 9 Figure a 17). Additionally, there were discrepancies across country groups, with workers in Nordic countries consistently reporting more often support compared to those in other European countries. However, in 2021, these differences across country groups have decreased significantly (Annex 9 Figure a 17).

The share of workers receiving support at work varies depending on their occupation, especially evident in 2005 when 75% of managers and skilled agricultural workers reported support at work compared to 93% of technicians and clerical support workers. However, as of 2021, the quasi totality of workers across all occupations (more than 94%) reported receiving support at work (Annex 9 Figure a 18).

Consulted at work

The percentage of individuals who are consulted in their workplace has experienced a substantial increase from 78% in 2015 to 92% in 2021 (Figure 11). Furthermore, respondents with higher levels of education were more likely to report being consulted at work compared to those with lower levels of education (Figure 11). If all workers reported being consulted more often in 2021 than in 2015, the share of persons indicating being consulted at work is especially high for managers, services and sale workers and professionals (Annex 9 Figure a 19). The lowest share is observed for craft workers and plant and machine operators.

Figure 11. Consulted at work



Note: Aggregated indicator based on Q61c and Q61d, representing different types of consultations at work. All the questions have been rescaled to binary indicators indicating if the person is being consulted (0 No - 1 Yes). The share of persons indicating they are being consulted at work is the share of observations for which the sum of these binary indicators is greater than 0. EWCS weighted data for all EU-27 countries.

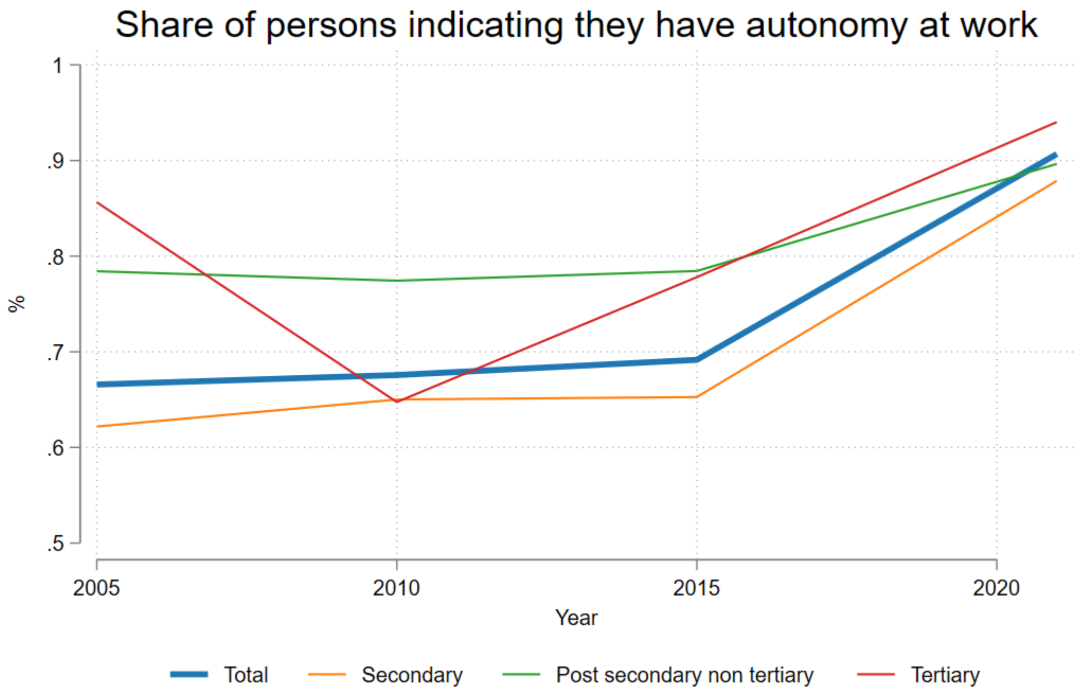
Autonomy

In the absence of direct measures of work motivation, we use autonomy as a proxy for work motivation in our analysis. However, we acknowledge that this approach may not capture all aspects of work motivation.

The proportion of respondents reporting having autonomy at work has increased from 70% in 2015 to 90% in 2021[5] (Figure 12). There is a discrepancy in the percentage of workers who report having autonomy at work based on their education level. In particular, those with a lower education level (secondary level) reported less autonomy compared to those with post-secondary non-tertiary education. However, workers with tertiary education reported having higher levels of autonomy in 2005 and 2021, but interestingly, had the lowest level of autonomy in 2010 (as depicted in Figure 12).

[5] This sharp increase in 2021 could partly be due to the rescaling of the indicator. In 2021, frequencies were asked (from 'never' to 'always') whereas for the previous surveys, the respondents already had a dichotomous question 'Yes'-'No'.

Figure 12. Autonomy at work indicator



Note: Aggregated indicator based on Q54a, Q54b and Q54c, representing different types of autonomy at work. All the questions have been rescaled to binary indicators indicating if the person has autonomy (0 No - 1 Yes). The share of persons indicating they have some autonomy at work is the share of observations for which the sum of these binary indicators is greater than 0. EWCS weighted data for all EU-27 countries.

Workers in the other services and public services and education sectors consistently reported higher levels of autonomy compared to those in construction, transportation, and storage sectors. Notably, there has been a significant increase in the percentage of workers indicating autonomy at work across all sectors from 2015 to 2021 (Annex 9 Figure a 20). Furthermore, workers in Nordic countries consistently reported higher levels of autonomy compared to those in other country groups across all sectors (Annex 9 Figure a 20).

Lastly, there are discrepancies across occupations with managers reporting higher levels of autonomy at work since 2005 compared to plant and machine operators who reported less often autonomy from 2005 to 2021. The share of plant and machine operators reporting having autonomy at work increased significantly compared to other occupations, notably rising from 47% in 2015 to 80% in 2021.

5 Estimating the relationship between job quality,[6] digitalisation, automation, artificial intelligence and offshoring

This section explores the relationship between job quality and digital transformation and off-shoring, using the latest wave of EWCS data (2021).

5.1 Poor safety at work, ergonomic and environmental risks at work[7]

Poor safety at work

The findings in Table 1 indicate a significant negative AME for advanced digital technologies, implying an inverse association between the risk of poor safety at work and the level of digitalisation (ADT). This finding suggests that the use of advanced digital technologies is likely to improve employees' self-perceived safety in the workplace. The standardisation of safety protocols across the organisation, facilitated by digital investments, along with the use of predictive analytics, contributes to proactive safety management, ultimately reducing the likelihood of safety breaches. Indeed, the adoption of advanced monitoring and surveillance systems, empowered by digital technologies, enables real-time identification of safety hazards and prompt interventions. Communication platforms facilitate the exchange of information and the reporting of incidents (Babalola *et al.*, 2023). Additionally, the ability to collect and analyse large amounts of safety-related data allows organisations to identify trends and implement targeted safety measures. Digitalisation may further support remote work arrangements, minimising employees' exposure to hazardous environments. Comparing different sub-groups of workers, this negative AME appears only for the workers aged 16-34, men and those of higher education group.

There is no evidence of significant causal relationship between automation risk and poor safety at work at the whole sample level. Nevertheless, comparing different sub-groups of workers a negative impact of automation appears for women and a positive causal impact for the workers aged 16-34 and men. Related literature focused on robotisation yields contrasting results regarding the link with workplace safety. Indeed, while Anton *et al.* (2020) demonstrate no

[6] Due to the large amount of missing data, the social dialogue dimension is not investigated in this part.

[7] The studied indicator of poor safety at work is based on the employee's self-perceived safety risk at work, compared to the mean safety risk at the occupation level. It takes the value 1 if the employee perceives the safety risk to be larger than the mean risk of their occupation, 0 otherwise.

effect of robotisation on workplace safety, other studies show that robotisation reduces the risk of work-related injuries (Gunadi & Ryu, 2021; Li & Singleton, 2021).

The exposure to artificial intelligence is not significant at the whole sample level but a negative link is revealed for certain socio-demographic sub-groups. Indeed, we find a significant negative effect of artificial intelligence for the group aged 16-34, men, and those with low education levels. As stated above, advances in AI are facilitating the standardisation of safety protocols across organisations and thus improve the safety of workers. Nevertheless, the links identified here may also suggest that some jobs, particularly for the low educated, are being replaced by digital advancement (Georgieff & Milanez, 2021), that may encourage workers who remain employed to retrain for safer jobs.

Table 1. Regression findings of technological changes on poor safety at work and poor treatment at work

	All	Age			Gender		Education		
		16-34	35-54	55+	Women	Men	Low	Medium	High
Poor safety at work									
Advanced digital technologies	-0.061**	-0.101**	-0.035	-0.075	-0.051	-0.075*	-0.034	-0.104	-0.093**
	(0.028)	(0.048)	(0.038)	(0.073)	(0.037)	(0.044)	(0.046)	(0.091)	(0.037)
Automation	0.262	0.940**	0.028	-0.118	-0.590*	1.360***	-0.021	-0.359	0.790
	(0.268)	(0.474)	(0.373)	(0.737)	(0.339)	(0.430)	(0.355)	(0.780)	(0.506)
Artificial intelligence	-0.071	-0.247***	-0.009	0.082	0.006	-0.200***	-0.167***	0.100	0.024
	(0.044)	(0.073)	(0.062)	(0.127)	(0.061)	(0.068)	(0.064)	(0.134)	(0.069)
Observations	8,008	2,584	4,265	1,159	4,872	3,136	3,279	550	4,179
Poor treatment at work									
Advanced digital technologies	0.037*	-0.002	0.045	0.084*	0.032	0.037	0.018	0.038	0.043*
	(0.021)	(0.039)	(0.028)	(0.047)	(0.026)	(0.035)	(0.031)	(0.077)	(0.026)
Automation	1.715***	1.166	2.128***	0.913	1.941***	1.349**	2.141***	1.978*	0.821
	(0.407)	(0.727)	(0.540)	(1.056)	(0.521)	(0.657)	(0.544)	(1.107)	(0.745)
Artificial intelligence	-0.108***	-0.075	-0.139***	0.013	-0.081**	-0.138***	-0.115***	-0.35***	-0.010
	(0.030)	(0.058)	(0.041)	(0.064)	(0.039)	(0.051)	(0.042)	(0.111)	(0.046)
Observations	5,233	1,696	2,793	671	3,215	2,018	2,159	356	2,718

Note: EWCS 2021, robust standard errors clustered at individuals in parentheses. * p<0.05, ** p<0.01, *** p<0.001. Separate regressions for each of the digital transformations measures. All regressions include controls for age, gender, education, dummy for part-time, having children, permanent contract, types of task, sector, firm size, country, one of the three digital transformation measure and exposure to offshoring. Average Marginal Effects (AMEs) of Advanced Digital Technologies (ADT) and Artificial Intelligence (AI) from Probit regressions and from IV for automation are reported.

5.2 Poor treatment at work

Results in Table 1 indicate that advanced digital technologies is slightly significantly and positively associated with poor treatment at work for the whole sample and for two socio-demographic sub-groups: 55 years and more, and high educated workers. This result contrasts with Melzer and Diewald (2020) who find that the Cyber-physical system or the Industry 4.0 are negatively related to the risk of harassment form the supervisor.

Our analysis reveals a strong, positive, and significant causal effect of automation on poor treatment at work. It suggests that automation, by reducing social interactions in the workplace (Smith & Anderson, 2014), may lead to poor communication that could, in turn, contributes to a negative work atmosphere. However, there is strong heterogeneity according to socio-demographic groups: automation increases the risk of poor treatment at work for both gender, those aged 35-54, and those with low or medium education.

Table 1 also shows that AI is significantly and negatively linked to poor treatment for employees aged 35-54, both genders and with low to medium education. By saving time on cognitive routine tasks (Arntz *et al.*, 2023), workers have more time to socialise with colleagues.

5.3 Working time satisfaction, high speed at work and work-life balance

Working time satisfaction

Findings in Table 2 indicate that at the whole sample level only the exposure to AI is positively and slightly significantly linked to employees' self-perceived working time satisfaction. This can be explained by the fact that AI-powered scheduling systems can efficiently allocate work hours based on employee preferences and workload demands. By taking into account individual preferences, employees are more likely to have schedules that align with their personal needs, leading to increased working time satisfaction. AI can also help streamline tasks, prioritise work, and reduce time spent on routine tasks (Arntz *et al.*, 2023), leading to a better perception of time management. Comparing different sub-groups of workers, this positive link is only observed for those aged 35-54.

We find a statistically significant and negative causal effect of automation but only for those aged 35-54 and women.

High speed at work

Table 2 shows positive and significant link between advanced digital technologies and high speed at work. However, this link is significant only for women and those aged 16-34. We also find a significant and negative causal effect of automation on high speed at work. Male employees, those aged 35-54 and of medium to high education operating in high automatable occupations are likely to have less issue with high speed at work. Artificial intelligence is positively and significantly link to high speed at work. This can lead to workers taking on more tasks, which in turn requires them to work faster to meet deadlines (Georgieff & Hyee, 2021). Seven out of eight socio-demographic sub-groups are affected by this positive and significant association: those aged 16 to 54, both genders, all levels of education.

Work-life balance

Table 2 shows no significant association between advanced digital technologies and work-life balance at the whole sample but positive links for two socio-demographic sub-groups: those aged 55 and more, and women.

We find that automation has a strong and negative causal effect on work-life balance. This suggests that workers in highly automatable occupations suffer harm to their work-life balance. The causal effects are significant for all socio-demographic sub-groups. It has been shown that employees' thinking that their current jobs could be replaced by robotics and algorithms is negatively related to organisational commitment and job satisfaction, and positively related to turnover intentions, cynicism and depression (Brougham & Haar, 2018), which can also affect work-life balance. On contrary, we find that AI is positively and significantly associated to work-life balance for the whole sample and all socio-demographic sub-groups. AI can improve work-life balance by increasing productivity, automating repetitive tasks, and enabling flexible working arrangements.

Table 2. Regression findings of technological changes on working time satisfaction, high speed at work and work-life balance

	All		Age		Gender			Education	
		16-34	35-54	55+	Women	Men	Low	Medium	High
Working time satisfaction									
Advanced digital technologies	0.036	0.043	0.033	0.029	0.053	0.026	0.042	-0.031	0.026
	(0.026)	(0.045)	(0.036)	(0.070)	(0.035)	(0.042)	(0.043)	(0.093)	(0.036)
Automation	-0.263	0.302	-0.636*	-0.371	-0.652*	0.262	-0.595	-0.480	0.448
	(0.277)	(0.493)	(0.380)	(0.767)	(0.357)	(0.442)	(0.362)	(0.714)	(0.522)
Artificial intelligence	0.101**	0.015	0.151***	0.159	0.088	0.087	0.087	0.143	0.089
	(0.042)	(0.068)	(0.059)	(0.121)	(0.058)	(0.064)	(0.060)	(0.139)	(0.065)
Observations	8,008	2,584	4,265	1,159	4,872	3,136	3,279	550	4,179
High speed at work									
Advanced digital technologies	0.049**	0.096**	0.029	0.032	0.082***	0.005	0.059	0.113	0.040
	(0.022)	(0.040)	(0.030)	(0.052)	(0.028)	(0.036)	(0.037)	(0.078)	(0.027)
Automation	-0.878***	-0.817	-1.024**	-0.437	-0.618	-1.325***	-0.270	-1.434*	-1.426**
	(0.302)	(0.518)	(0.425)	(0.812)	(0.387)	(0.465)	(0.398)	(0.757)	(0.560)
Artificial intelligence	0.182***	0.133**	0.247***	0.040	0.161***	0.170***	0.171***	0.228**	0.164***
	(0.035)	(0.060)	(0.049)	(0.083)	(0.046)	(0.055)	(0.051)	(0.114)	(0.051)
Observations	8,008	2,584	4,265	1,159	4,872	3,136	3,279	550	4,179
Work-life balance									
Advanced digital technologies	0.036	0.029	0.022	0.111**	0.068**	0.006	0.042	0.120	0.036
	(0.023)	(0.040)	(0.032)	(0.054)	(0.031)	(0.035)	(0.038)	(0.080)	(0.029)
Automation	-1.674***	-1.679***	-1.325***	-2.882***	-1.803***	-1.454***	-1.285***	-2.152***	-1.958***
	(0.294)	(0.512)	(0.408)	(0.760)	(0.365)	(0.459)	(0.390)	(0.802)	(0.544)
Artificial intelligence	0.208***	0.286***	0.133***	0.306***	0.197***	0.194***	0.175***	0.317***	0.205***
	(0.035)	(0.059)	(0.051)	(0.083)	(0.049)	(0.052)	(0.053)	(0.111)	(0.051)
Observations	7,990	2,579	4,255	1,156	4,858	3,132	3,272	548	4,170

Note: EWCS 2021, robust standard errors clustered at individuals in parentheses. * p<0.05, ** p<0.01, *** p<0.001. Separate regressions for each of the digital transformations measures. All regressions include controls for age, gender, education, dummy for part-time, having children, permanent contract, types of task, sector, firm size, country, one of the three digital transformation measure and exposure to offshoring. Average Marginal Effects (AMEs) of Advanced Digital Technologies (ADT) and Artificial Intelligence (AI) from Probit regressions and from IV for automation are reported.

5.4 Job insecurity

Table 3 shows that advanced digital technologies have no significant association with job insecurity, measured as the employees' self-perceived risk of losing job at the whole sample and socio-demographic sub-groups except a negative link for those aged 16-34 is revealed. To our knowledge, most studies suggest positive link between digitalisation and job insecurity (Martin & Hauret, 2022). Some others highlight a negative relationship (Caselli *et al.*, 2021).

Regarding automation, our results do not reveal any significant effects for the whole sample and socio-demographic sub-groups except medium educated workers. This is in line with a recent analysis on Italian workers by Nazareno and Schiff (2021) showing that automation and job security are not strongly related. For the medium level of education, we find a significant positive causal effect of automation. This finding is consistent with analyses highlighting that digital transformation has induced routine-replacing technological change (RRTC), which polarises the labour market and causes middle-skilled workers to suffer most of the job losses (e.g. Autor, Levy & Murnane, 2003; Goos, Manning & Salomons, 2009, 2014; Acemoglu & Autor, 2011; Michaels, Natraj & Van Reenen, 2014). This has been an ongoing process since the early 1980s (Cortes, 2016) and has emerged in both Europe and the United States (Darvas & Wolff, 2016).

We also find that AI is negatively and significantly associated with job insecurity, especially for those of the medium level of education. The negative association between AI and job insecurity, particularly for medium-skilled workers, may be due to the fact that these workers are more likely to be in occupations that are susceptible to automation rather than AI. It is also possible that AI will lead to the creation of new jobs and opportunities for medium-skilled workers, as well as the retraining and upskilling of existing workers to perform new tasks.

5.5 Self-perceived fair pay

Advanced digital technologies have a significant and positive association with this job quality indicator (Table 3), that appear for the whole sample and for those aged 55 and more, women and those with medium and high level of education.

Table 3. Regression findings of technological changes on job insecurity, self-perceived fair pay and training paid by employer

	All	Age			Gender		Education		
		16-34	35-54	55+	Women	Men	Low	Medium	High
Job insecurity									
Advanced digital technologies	-0.021	-0.074**	0.015	-0.049	-0.029	-0.020	-0.014	-0.085	-0.034
	(0.021)	(0.037)	(0.030)	(0.046)	(0.027)	(0.033)	(0.035)	(0.068)	(0.026)
Automation	0.024	0.848	-0.430	0.055	-0.045	0.185	-0.616	1.932**	0.558
	(0.335)	(0.584)	(0.466)	(0.966)	(0.421)	(0.542)	(0.443)	(0.824)	(0.583)
Artificial intelligence	-0.066**	-0.085	-0.060	-0.031	-0.069	-0.026	-0.055	-0.260***	-0.016
	(0.032)	(0.053)	(0.046)	(0.075)	(0.043)	(0.049)	(0.048)	(0.098)	(0.044)
Observations	7,827	2,545	4,158	1,124	4,765	3,062	3,194	529	4,104
Self-perceived fair pay									
Advanced digital technologies	0.065*	0.077	0.022	0.236***	0.077*	0.076	-0.006	0.232*	0.105**
	(0.034)	(0.059)	(0.048)	(0.085)	(0.045)	(0.053)	(0.056)	(0.120)	(0.044)
Automation	-0.338	-0.799	-0.163	0.409	0.084	-0.979*	-0.665	-0.226	0.372
	(0.332)	(0.571)	(0.460)	(0.995)	(0.428)	(0.532)	(0.430)	(0.881)	(0.643)
Artificial intelligence	0.061	0.077	0.072	-0.001	0.038	0.091	0.149*	-0.187	-0.021
	(0.054)	(0.093)	(0.076)	(0.143)	(0.076)	(0.082)	(0.079)	(0.182)	(0.083)
Observations	5,390	1,720	2,883	787	3,258	2,132	2,171	368	2,851
Training paid by employer									
Advanced digital technologies	0.070**	0.098*	0.091*	0.013	0.078*	0.082	0.047	0.097	0.070
	(0.034)	(0.059)	(0.048)	(0.087)	(0.045)	(0.053)	(0.055)	(0.116)	(0.046)
Automation	-0.454	-1.089*	-0.456	1.026	-0.230	-0.729	-0.249	0.627	-0.996
	(0.328)	(0.578)	(0.454)	(0.892)	(0.422)	(0.522)	(0.428)	(0.856)	(0.638)
Artificial intelligence	0.230***	0.252***	0.233***	0.114	0.202***	0.279***	0.280***	-0.137	0.262***
	(0.054)	(0.093)	(0.076)	(0.141)	(0.075)	(0.081)	(0.077)	(0.179)	(0.086)
Observations	5,410	1,726	2,891	793	3,266	2,144	2,186	370	2,854

Note: EWCS 2021, robust standard errors clustered at individuals in parentheses. * p<0.05, ** p<0.01, *** p<0.001. Separate regressions for each of the digital transformations measures. All regressions include controls for age, gender, education, dummy for part-time, having children, permanent contract, types of task, sector, firm size, country, one of the three digital transformation measure and exposure to offshoring. Average Marginal Effects (AMEs) of Advanced Digital Technologies (ADT) and Artificial Intelligence (AI) from Probit regressions and from IV for automation are reported.

This result suggests that digitalisation may increase some employees' self-perceived fair pay. This result may be explained by the fact that digitalisation often requires a shift in the skill set needed for certain job roles. Digitalisation in certain tasks rises the skill premium (Burstein *et al.*, 2019) that may affect the self-perceived fair pay gap of certain groups of workers.

The results show any significant links with automation and AI for the whole sample and socio-demographic sub-groups except a negative impact of automation for men and a positive link with AI for low educated workers.

5.6 Training paid by the employer

Table 3 indicates a positive and significant association between advanced digital technologies and training paid by the employer (Brunello *et al.*, 2022). There are no differentiated effects among socio-demographic sub-groups except for those aged from 16 to 54 and women.

Automation has no causal effect on training paid by employer, except for workers aged 16-34. As underlined by Aksoy *et al.* (2018), many countries face significant gaps in the quality of technology-related skills, particularly among older workers. Our results suggest that firms are trying to overcome this specific skills shortage.

We also find that employees working in occupations with high exposure of AI are more likely to receive training paid by employers This result holds for all socio-demographic sub-groups, except for the over-55s and the medium education group. These results suggest that as AI-driven systems necessitate employees to acquire new skills, employers can be more inclined to offer training programs to ensure the effective operation and utilisation of these technologies. The results also highlight that older workers and middle-skilled workers do not always benefit from these measures. Our results are in line with those of other studies that show an upskilling of existing employees within the company following the introduction of (Grande *et al.*, 2021). Finally, professions that have a high risk of being replaced by digitalisation are probably those that require a medium level of education. Higher educated individuals are more likely to undergo training compared to others (Kleinert & Wölfel, 2018).

5.7 Employment-related relationships

Autonomy at work

Results reported in Table 4 indicate positive and significant association of advanced digital technologies with autonomy at work, especially for those workers aged 16-34, women and those with a medium level of education. Literature stresses the fact that the relationship between digitalisation and work autonomy depends on the type of technology used. For example, while information technologies provide more autonomy to employees, communication technologies tend to increase the centralisation of the decision making process (Bloom *et al.*, 2014; Eisele & Schneider, 2020; Gerten *et al.*, 2019; Martin, 2017).

We also find that automation has a negative and strongly significant causal effect on autonomy at work. There are however no heterogeneous effects according to socio-demographic sub-groups. This result supports the hypothesis that automated systems, driven by predefined algorithms and real-time decision making capabilities, optimise efficiency and productivity but limit employees' flexibility in task sequencing and alternative approaches. While streamlining workflows and minimising delays enhances organisational efficiency, it may restrict employees' autonomy in determining task order and pace. Additionally, automated processes with minimal human intervention further diminish employees' ability to influence work methods, exacerbating the reduction in autonomy (Bobillier Chaumon *et al.*, 2014).

Table 4 also shows that AI is positively and significantly associated with autonomy at work, especially for workers aged less than 54, both gender and all education levels. The use of AI makes it possible to automate some tasks that previously required several workers. This can give individual workers more autonomy.

Table 4. Regression findings of technological changes on autonomy, support at work and consulted at work

	All		Age		Gender			Education	
		16-34	35-54	55+	Women	Men	Low	Medium	High
Autonomy									
Advanced digital technologies	0.051**	0.112***	0.032	0.010	0.076**	-0.002	0.028	0.206***	0.042
	(0.023)	(0.040)	(0.030)	(0.058)	(0.030)	(0.036)	(0.039)	(0.073)	(0.027)
Automation	-2.429***	-3.047***	-2.439***	-1.390*	-2.092***	-2.937***	-2.038***	-2.933***	-2.870***
	(0.311)	(0.520)	(0.443)	(0.836)	(0.391)	(0.473)	(0.405)	(0.761)	(0.587)
Artificial intelligence	0.208***	0.294***	0.205***	0.062	0.111**	0.314***	0.240***	0.264**	0.162***
	(0.034)	(0.060)	(0.046)	(0.091)	(0.047)	(0.053)	(0.055)	(0.112)	(0.042)
Observations	8,008	2,584	4,265	1,159	4,872	3,136	3,279	550	4,179
Organisational support									
Advanced digital technologies	0.010	-0.009	0.016	0.037	-0.003	0.017	0.012	0.019	0.017
	(0.012)	(0.016)	(0.016)	(0.041)	(0.015)	(0.018)	(0.021)	(0.038)	(0.013)
Automation	-1.174**	-0.880	-1.585**	-0.410	-0.867	-1.908**	-1.191**	-2.150	-0.766
	(0.482)	(0.940)	(0.626)	(1.233)	(0.589)	(0.743)	(0.602)	(1.420)	(0.904)
Artificial intelligence	0.052***	0.056**	0.044*	0.102	0.032	0.083***	0.045	0.109**	0.055***
	(0.018)	(0.023)	(0.024)	(0.063)	(0.022)	(0.028)	(0.028)	(0.055)	(0.021)
Observations	8,008	2,584	4,265	1,159	4,872	3,136	3,279	550	4,179
Consulted at work									
Advanced digital technologies	0.032	0.039	0.037	0.020	0.034	0.039	0.035	-0.001	0.044**
	(0.020)	(0.036)	(0.027)	(0.052)	(0.025)	(0.033)	(0.036)	(0.065)	(0.023)
Automation	-1.156***	-0.931	-1.261***	-1.350	-0.831**	-1.752***	-1.446***	-1.280	-0.813
	(0.332)	(0.605)	(0.448)	(0.935)	(0.422)	(0.523)	(0.426)	(0.808)	(0.652)
Artificial intelligence	0.185***	0.166***	0.072*	0.246***	0.051	0.211***	0.174***	0.134	0.080**
	(0.023)	(0.052)	(0.043)	(0.084)	(0.040)	(0.050)	(0.050)	(0.106)	(0.040)
Observations	8,008	2,584	4,265	1,159	4,872	3,136	3,279	550	4,179

Note: EWCS 2021, robust standard errors clustered at individuals in parentheses. * $p<0.05$, ** $p<0.01$, *** $p<0.001$. Separate regressions for each of the digital transformations measures. All regressions include controls for age, gender, education, dummy for part-time, having children, permanent contract, types of task, sector, firm size, country, one of the three digital transformation measure and exposure to offshoring. Average Marginal Effects (AMEs) of Advanced Digital Technologies (ADT) and Artificial Intelligence (AI) from Probit regressions and from IV for automation are reported.

Organisational support

The findings reported in Table 4 do not provide any evidence of a significant association between advanced digital technologies with support at work. Regarding new technologies, literature yields mixed effects. Some studies emphasise that new technologies improve social support between co-workers (Martin & Omrani, 2015; Castellacci & Viñas-Bardolet, 2019), while others conclude that they accentuate tensions among co-workers (Askenasy & Caroli, 2010).

Table 4 also shows that automation has a significant and negative causal effect on support at work, especially for those workers aged 35-54, male and those with low education.

Regarding AI, results in Table 4 show that workers in occupations with high risk of AI are more likely to perceive support at work, as there is positively and significantly association between AI and support at work. Especially for workers aged below 55, men and workers with medium to higher education.

Consulted at work

Table 4 underlines that advanced digital technologies have any significant association with consultation except for high-educated workers. Results in Table 4 show that automation is significantly and negatively associated with reduced employee consultation on work objectives. This supports the fact that automated systems rely on standardised processes and predetermined objectives, often set by higher-level management or based on predefined performance metrics. The efficiency and speed of automation may lead to real-time or near-real-time objective decisions, leaving limited room for extensive consultation with individual employees. Moreover, automated systems generally operate without direct human intervention, further reducing opportunities for employee consultation (and autonomy at shown above). These results hold particularly for the middle-aged workers (group 35-54), both gender and workers with low education. There is, nevertheless, a gender difference as the causal effect for men is stronger than for women.

The marginal effects of AI are positive and significant for the whole sample and all ages, men, and workers with low or high educations levels.- In line with the results related to autonomy, the AI exposure appears beneficial to many workers.

5.8 Offshoring risk

Our study differs from existing papers (Nikulin *et al.*, 2022; Parteka *et al.*, 2023; Grimm, 2023) in terms of the digital transformation measures and job quality measures used. Therefore, our results shown in Table 6 provide new evidence that has not been previously reported in the literature. Exposure to offshoring is significantly and negatively associated with three measures of job quality, regardless of the digital transformation measure introduced in the regressions: poor safety at work, poor treatment at work, and training paid for by the employer. According to Nikulin *et al.* (2022), AI differs significantly from other digital transformation measures when examining its relationship with job quality. Our analyses found that two measures of job quality, work at high speed and work-life balance, are positively associated with exposure to offshoring when controlling for advanced digital technologies or automation, but not when controlling for artificial intelligence. Exposure to offshoring does not appear to be related to three measures of job quality: satisfaction with working time, job security, and self-perceived fair pay.

Our results point out that offshoring has both positive and negative effects on workers. On the positive side, it reduces poor safety and poor treatment at work, and improves work-life balance. This may be due to the fact that low-quality jobs may already be offshored. On the negative side, offshoring is positively related to working at a high speed pace and reduces the amount of training provided by employers. This lack of training may limit their access to jobs that are less exposed to offshoring.

Table 5. Regression findings of offshoring on job quality

	Obs.	Advanced digital technologies	Automation	Artificial intelligence
Poor safety at work	8,008	-0.106***	-0.279***	-0.097***
		(0.029)	(0.074)	(0.030)
Poor treatment at work	5,233	-0.081***	-0.424***	-0.053**
		(0.022)	(0.127)	(0.024)
Working time satisfaction	8,008	-0.021	-0.040	-0.039
		(0.028)	(0.076)	(0.029)
High speed at work	8,008	0.039*	0.160*	0.008
		(0.022)	(0.082)	(0.024)
Work-life balance	7,990	0.058**	0.223***	0.022
		(0.024)	(0.082)	(0.025)
Job insecurity	7,827	-0.013	-0.059	-0.002
		(0.021)	(0.089)	(0.023)
Self-perceived fair pay	5,390	0.041	0.113	0.035
		(0.036)	(0.092)	(0.038)
Training paid by employer	5,410	-0.081**	-0.164*	-0.120***
		(0.036)	(0.091)	(0.038)

Note: EWCS 2021, robust standard errors clustered at individuals in parentheses. * $p<0.05$, ** $p<0.01$, *** $p<0.001$. Separate regressions for each of the digital transformations measures. All regressions include controls for age, gender, education, dummy for part-time, having children, permanent contract, types of task, sector, firm size, country, one of the three digital transformation measure and exposure to offshoring. Average Marginal Effects (AMEs) of Advanced Digital Technologies (ADT) and Artificial Intelligence (AI) from Probit regressions and from IV for automation are reported.

6 Conclusion

This report analyses the impact of digital transformation and globalisation on job quality, with a specific focus on advanced digital technologies (ADT), automation risk, and exposure to artificial intelligence (AI). We use the most recent EWCS survey for European countries and external data sources for digital transformation and globalisation.

The report focuses on various indicators of job quality, including poor safety at work, poor treatment at work, satisfaction with working time, job insecurity, fair pay, and organisational support, consultation at work, training, and autonomy. The descriptive part shows that over the period from 2005-2021 job quality has improved along several dimension, notably in the realms of social dialogue access and perceptions of fair compensation. Significantly, the proportion of employees who believe their pay is fair has risen from approximately 40% in 2005 to just under 60% in 2021, with the most marked improvements seen among those with lower educational levels. Job security has reached its highest point since 2005. Moreover, the percentage of workers receiving employer-sponsored training has nearly doubled, from 25% in 2005 to 45% in 2021, cutting across all age brackets, including those over 55 years. Workplace support has seen a substantial increase, with 97% of employees in 2021 reporting access to support, a substantial rise from 86% in 2005. Furthermore, employee consultation at work has also seen a similar upward trend. On the negative side, there have been declines in aspects like fair treatment and satisfaction with working hours, although there's a slight uptick in perceived work-life balance.

The analysis of the correlation and causal effects reveals several results. First, the adoption of ADT may improve job quality, particularly for younger and older workers. Hence, the adoption of ADT has an inverse relationship with poor safety at work, ergonomic, and environmental risks, especially among younger workers (16-34) and those with higher education. Furthermore, ADT is positively associated with high work speed, particularly among younger workers (16-34) and women. The study found that ADT is positively and significantly correlated with self-perceived fair pay for older workers (aged 55 and over) and those with medium to high levels of education. Additionally, there is a positive, albeit slightly significant, correlation between ADT and training. Furthermore, young workers aged 16-34 and those with a medium level of education working in sectors with high ADT are more likely to have higher autonomy as the association is positive and significant. The data indicates that older workers aged 55 and women employed in sectors with high levels of ADT are more likely to experience a better work-life balance. No significant correlation was found between the other job quality indicators, namely satisfaction with working hours, job insecurity, and receiving consultation and support from colleagues.

Second, the IV estimation results suggest a causal association between automation and adverse effects on workers' experiences. The negative impact on work-life balance implies that automated processes may disrupt the equilibrium between professional and personal life. Additionally, the diminished autonomy suggests that automation might limit the control and independence workers have in their tasks. The potential negative impact of automation on organisational support and workplace consultation suggests that it may result in reduced support structures and communication channels, leaving workers feeling disengaged and excluded from decision making processes. It is important to note that these effects are not uniform across all socio-demographic sub-groups. On the contrary, no significant causality has been found between automation and other job quality indicators, such as poor safety at work, satisfaction with working hours, fair pay, and employer-paid training. In line with analyses highlighting that automation has induced routine-replacing technological change (RRTC), medium-skilled workers are particularly at risk of experiencing low job quality due to automation. This is because they are more likely to have higher job insecurity and perceive poor treatment at work.

Third, exposure to AI is generally beneficial for workers as it is positively and significantly associated with employees' self-perceived satisfaction with their working hours, work-life balance, and access to employer paid training. AI is also negatively and significantly associated with poor treatment, ergonomic and environmental risks at work, and job insecurity. However, this comes at the cost of working at a high speed. The sample as a whole does not show significant exposure to artificial intelligence regarding poor safety at work or self-perceived fair pay.

With regard to offshoring, the results underline that exposure to offshoring is positively associated with safety at work, fair treatment and work-life balance, but negatively associated with training.

Overall, there has been a positive development in most indicators of job quality since 2005. Digitalisation and globalisation have varying effects on different aspects of job quality. There may be risks to job quality from trends in digitalisation, AI and offshoring, but until now, we show that there is no clear picture that these trends are in general affecting job quality negatively.

References

Acemoglu, D., and David H. Autor, D. H. (2011). Skills, Tasks and Technologies: Implications for Employment and Earnings. In *Handbook of Labor Economics*, eds. David Card and Orley C. Ashenfelter. Elsevier Inc., 1043–1171.

Akinlolu, M. *et al.* (2020). A bibliometric review of the status and emerging research trends in construction safety management technologies. *International Journal of Construction Management*, 1–13. https://doi.org/10.1080/ 15623599.2020.1819584

Aksoy, C. G., Barrero, J. M., Bloom, N., Davis, S. J., Dolls, M., & Zarate, P. (2022). Working from home around the world. *NBER Working Paper No 30446*. https://doi.org/10.2139/ssrn.4219442

Aksoy, C. G., Giesing, Y., Laurentsyeva, N., & Wirsching, E. (2018). ‘Skills, employment and automation.’ In Transition Report 2018-19: Work in Transition, European Bank for Reconstruction and Development (EBRD), 54–77.

Aksoy, C. G., Ozcan, B., & Philipp, J. (2020). Robots and the gender pay gap in Europe. *IZA Discussion Paper No 13482*, 1–32.

Anton, E., Behne, A., & Teuteberg, F. (2020). The humans behind artificial intelligence: An operationalisation of AI competencies. *Proceedings of the 28th European Conference on Information Systems (ECIS), Online AIS Conference*.

Anton, J.-I., Fernandez-Macias, E., & Winter-Ebmer, R. (2020). Does robotization affect job quality? Evidence from European regional labour markets. *CEPR Discussion Paper No 15586*.

Antràs, P., Garicano, L., & Rossi-Hansberg, E. (2006). Offshoring in a knowledge economy. *Quarterly Journal of Economics*, *121*(1), 31–77. https://doi.org/10.1162/003355306776083527

Arlinghaus, A., & Nachreiner, F. (2013). When work calls-associations between being contacted outside of regular working hours for work-related matters and health. *Chronobiology International*, *30*(9), 1197–1202. https://doi.org/10.3109/07420528.2013.800089

Arntz, M., Gregory, T. & Zierahn, U. (2017). Revisiting the risk of automation. *Economics Letters* 159, 157–60. http://dx.doi.org/10.1016/j.econlet.2017.07.001

Arntz, M., Genz, S., Gregory, T., Lehmer, F., & Zierahn-Weilage, U. (2023). De-routinization in the fourth industrial revolution - Firm-level evidence. *Mimeo*.

Askenazy, P., & Caroli, E. (2010). Innovative work practices, information technologies, and working conditions: Evidence for France. *Industrial Relations*, *49*(4), 544–565. https://doi.org/10.1111/j.1468-232X.2010.00616.x

Atalay, E., Phongthiengtham, P., Sotelo, S., & Tannenbaum, D. (2018). New technologies and the labor market. *Journal of Monetary Economics*, *97*, 48–67. https://doi.org/10.1016/j.jmoneco.2018.05.008

Autor, D. H., & Dorn, D. (2013). The growth of low-skill service jobs and the polarization of the US labor market. *American Economic Review*, *103*(5), 1553–1597. https://doi.org/10.1257/aer.103.5.1553

Autor, D. H., & Handel, M. J. (2013). Putting tasks to the test: Human capital, job tasks, and wages. *Journal of Labor Economics*, *31*(S1), S59–S96. https://doi.org/10.1086/669332

Autor, D. H., Levy, F., and Murnane, R. J. (2003). The skill content of re- cent technological change: An empirical exploration. *The Quarterly Journal of Economics*, 118(4), 1279–1333. https://doi.org/10.1162/003355303322552801

Ayyagari, R., Grover, V., & Purvis, R. (2011). Technostress: technological antecedents and implications. *MIS quarterly*, 35(4):831–858.

Babalola, A., Manu, P., Cheung, C., Yunusa-Kaltungo, A., & Bartolo, P. (2023) A systematic review of the application of immersive technologies for safety and health management in the construction sector. *Journal of Safety Research*, 85, 66-85. https://doi.org/10.1016/j.jsr.2023.01.007

Bachmann, R., Gonschor, M., Lewandowski, P., & Madoń, K. (2022). The impact of robots on labour market transitions in Europe. *IZA Discussion Paper No 15303*.

Baumgarten, D., Geishecker, I., & Görg, H. (2013). Offshoring, tasks, and the skill-wage pattern. *European Economic Review*, *61*, 132–152. https://doi.org/10.1016/j.euroecorev.2013.03.007

Blinder, A. S., & Krueger, A. B. (2013). Alternative measures of offshorability: A survey approach. *Journal of Labor Economics*, *31*(2), S97–S128. https://doi.org/10.1086/669061

Bloom, N., Garicano, L., Sadun, R., & Van Reenen, J. (2014). The distinct effects of information technology and communication technology on firm organization. *Management Science*, *60*(12), 2859–2885. https://doi.org/10.1287/mnsc.2014.2013

Bobillier Chaumon, M.-E.., Cuvillier, B., Sarnin, P. & Body-Bekkadja, S. (2014). Judicious use of ICT - Information and communications technologies (ICT) and the working conditions of professional and managerial staff (P&MS), Eurocadres, Research group in Ergonomics and Work Psychology (GREPSYT)

Brougham, D., & Haar, J. (2018). Smart technology, artificial intelligence, robotics, and algorithms (STARA): Employees' perceptions of our future workplace. *Journal of Management and Organization*, *24*(2), 239–257. https://doi.org/10.1017/jmo.2016.55

Brunello, G., Rückert, D., Weiss, C. T., and Wruuck, P. (2022). Advanced digital technologies and investment in employer training: Complements or substitutes ? *Mimeo*.

Brynjolfsson, E., Mitchell, T., & Rock. D. (2018). What can machines learn and what does it mean for occupations and the economy? *AEA Papers and Proceedings* 108: 43–47. https://doi.org/10.1257/pandp.20181019

Bucher, E., Fieseler, C., and Suphan, A. (2013). The stress potential of social media in the workplace. *Information, Communication & Society*, 16(10):1639–1667. https://doi.org/10.1080/1369118X.2012.710245

Burstein, A., Morales, E., and Vogel, J. (2019). Changes in between-group inequality: Computers, occupations, and international trade. *American Economic Journal: Macroeconomics*, 11(2): 348–400. https://doi.org/10.1016/10.1257/mac.20170291

Capello, R., Lenzi, C., & Panzera, E. (2023). The digital service economy as a source of intra-regional wage inequalities. *(Deliverable 4.7) Leuven: UNTANGLED Project 1001004776 – H2020.*

Caselli, M., Fracasso, A., Marcolin, A., & Scicchitano, S. (2021). The reassuring effect of firms' technological innovations on workers' job insecurity. GLO Discussion Paper No. 938.

Castellacci, F., & Viñas-Bardolet, C. (2019). Internet use and job satisfaction. *Computers in Human Behavior*, *90*, 141–152. https://doi.org/10.1016/j.chb.2018.09.001

Christiaens, T. (2023). Digital working lives – Worker autonomy and the gig economy. Rowman & Littlefield. London.

Cirillo, V., Rinaldini, M., Staccioli, J., & Virgillito, M. E. (2021). Technology vs. workers: the case of Italy's Industry 4.0 factories. *Structural Change and Economic Dynamics*, *56*, 166–183. https://doi.org/10.1016/j.strueco.2020.09.007

Ciullo, A. S., Catalano, M. G., Bicchi, A., & Ajoudani, A. (2021). A supernumerary soft robotic limb for reducing hand-arm vibration syndromes risks. Frontiers in Robotics and AI 8(August): 1–15. https://doi.org/10.3389/frobt.2021.650613

Clark, A. E. (2005). Your money or your life: Changing job quality in OECD countries. *British Journal of Industrial Relations*, *43*(3), 377–400. https://doi.org/10.1111/j.1467-8543.2005.00361.x

Cortes, G. M. (2016) Where Have the Middle-Wage Workers Gone? A Study of Polarization Using Panel Data. *Journal of Labor Economics*, 34(1), 63–105. https://doi.org/10.1086/682289

Cortes, G. M., Oliveira, A., & Salomons, A. (2020). Do technological advances reduce the gender wage gap? *Oxford Review of Economic Policy*, *36*(4), 903–924. https://doi.org/10.1093/oxrep/graa051

Crinò, R. (2009). Offshoring, multinationals and labour market: A review of the empirical literature. *Journal of Economic Surveys*, *23*(2), 197–249. https://doi.org/10.1111/j.1467-6419.2008.00561.x

Crinò, R. (2012). Service offshoring and the skill composition of labour demand. *Oxford Bulletin of Economics and Statistics*, *74*(1), 20–57. https://doi.org/10.1111/j.1468-0084.2010.00634.x

Currie, J., & Eveline, J. (2011). E-technology and work/life balance for academics with young children. *Higher Education*, *62*(4), 533–550. https://doi.org/10.1007/s10734-010-9404-9

Darvas, Z., and Wolff, G. B. (2016). *An Anatomy of Inclusive Growth in Europe*. Bruegel report

De La Rica, S., Gortazar, L., & Lewandowski, P. (2020). Job tasks and wages in developed countries: Evidence from PIAAC. *Labour Economics*, *65*(August). https://doi.org/10.1016/j.labeco.2020.101845

Dengler, K., and Matthes, B. (2018). The impacts of digital transformation on the labour market: Substitution potentials of occupations in Germany.' *Technological Forecasting and Social Change* 137(December): 304–16.

Derks, D., Bakker, A. B., Peters, P., & Van Wingerden, P. (2016). Work-related smartphone use, work-family conflict and family role performance: The role of segmentation preference. *Human Relations*, *69*(5), 1045–1068. https://doi.org/10.1177/0018726715601890

Domini, G., Grazzi, M., Moschella, D., & Treibich, T. (2020). For whom the bell tolls: the effects of automation on wage and gender inequality within firm. *Available at SSRN 3701517*. https://doi.org/10.2139/ssrn.3701517

Edin, P. A., Evans, T., Hernnäs, S., Graetz, G., & Michaels, G. (2021). Individual consequences of occupational decline. *IZA DP No. 12434*.

EIB. (2023). Resilience and renewal in Europe. *EIB Report*.

Eisele, S., & Schneider, M. R. (2020). What do unions do to work design? Computer use, union presence, and tayloristic jobs in Britain. *Industrial Relations*, *59*(4), 604–626. https://doi.org/10.1111/irel.12266

Eurofound. (2021). Working conditions and sustainable work: An analysis using the job quality framework Challenges and prospects in the EU. *Publications Office of the European Union, Luxembourg.*

Eurofound (2021) Impact of digitalisation on social dialogue and collective bargaining. *Publications Office of the European Union, Luxembourg.*

Eurofound (2023), Living and working in Europe 2022. *Publications Office of the European Union, Luxembourg*.

Eurofound and the International Labour Office (2017). Working anytime, anywhere: The effects on the world of work. *Publications Office of the European Union, Luxembourg, and the*

International Labour Office, Geneva.

European Commission High-Level Expert Group. (2019, April). The impact of the digital transformation on EU labour markets. *European Commission Report*, 1–52. https://doi.org/10.2759/365241

Falck, O., Heimisch-Roecker, A., & Wiederhold, S. (2021). Returns to ICT skills. *Research Policy*, *50*(7), 104064. https://doi.org/10.1016/j.respol.2020.104064

Felten, E. W., Manav, R., & Seamans, R. (2018). A method to link advances in Artificial Intelligence to occupational abilities. *AEA Papers and Proceedings* 108(May): 54–57.

Flèche, S., Moreno Galbis, E., Reshef, A., Rotunno, L., & Senik, C. (2023). Digitalisation and polarisation in nonpecuniary working conditions, *Mimeo*.

Gallie, D., Felstead, A., Green, F., & Inanc, H. (2017). The hidden face of job insecurity. *Work, Employment and Society*, *31*(1), 36–53. https://doi.org/10.1177/0950017015624399

Ge, S., & Zhou, Y. (2020). Robots, computers, and the gender wage gap. *Journal of Economic Behavior and Organization*, *178*, 194–222. https://doi.org/10.1016/j.jebo.2020.07.014

Genz, S., Gregory, T., Janser, M., Lehmer, F., & Matthes, B. (2021). How do workers adjust when firms adopt new technologies? *IZA Discussion Paper No 14626*.

Georgieff, A., & Milanez, A. (2021). What happened to jobs at high risk of automation?' OECD Social, Employment and Migration Working Papers No. 255. https://dx.doi.org/10.1787/10bc97f4-en

Georgieff, A.,& Hyee, R. (2021). Artificial intelligence and employment: New cross-country evidence. OECD Social, Employment and Migration Working Papers No. 265. https://dx.doi.org/10.1787/c2c1d276-en

Gerten, E., Beckmann, M., Bellmann, L. (2019). Controlling working crowds: The impact of digitalization on worker autonomy and monitoring across hierarchical levels. J Econ Stat 239:441–481. https://doi.org/10.1515/jbnst-2017-0154

Goos, M., Manning, A., and Salomons, A. S. (2009). Job polarization in Europe. *American Economic Review*, 99(2), 58–63. https://doi.org/10.1257/aer.99.2.58

Goos, M., Manning, A., and Salomons, A. S. (2014). 'Explaining job polarization: Routine-biased technological change and offshoring.' *American Economic Review*, 104(8), 2509–2526. https://doi.org/10.1257/aer.104.8.2509

Goos, M., Rademakers, E., & Röttger, R. (2021). Routine-Biased technical change: Individual-Level evidence from a plant closure. *Research Policy*, *50*(7), 104002. https://doi.org/10.1016/j.respol.2020.104002

Görg, H., & Görlich, D. (2015). Offshoring, wages and job security of temporary workers. *Review of World Economics*, *151*, 533–554. https://doi.org/10.2139/ssrn.2182557

Graetz, G., & Michaels, G. (2018). Robots at work. *The Review of Economics and Statistics*, *C*(5), 753–768. https://doi.org/10.1162/rest_a_00754

Grande, R., Vallejo-Peña, A., Urzi-Brancati, C. (2021). The impact of IoT and 3D printing on job quality and work organisation: a snapshot from Spain. *JRC Working Papers on Labour, Education and Technology 2021/10*, Joint Research Centre (Seville).

Grimm, F. (2023). Digital Technologies, Job Quality and Employer-Provided Training, *Mimeo*.

Gunadi, C., & Ryu, H. (2021). Does the rise of robotic technology make people healthier? *Health Economics*, 30(9):2047-2062. https://doi.org/10.1002/hec.4361

Harrison, A., & Mcmillan, M. (2011). Offshoring jobs? Multinationals and U.S. manufacturing employment. *Review of Economics and Statistics*, *93*(3), 857–875. https://doi.org/10.1162/REST_a_00085

Huang, L.-C., Ahlstrom, D., Lee, A. Y.-P., Chen, S.-Y., & Hsieh, M.-J. (2016). High performance work systems, employee well-being, and job involvement: an empirical study. *Personnel Review*, *45*(2), 296–314. https://doi.org/10.1108/PR-09-2014-0201

Hudomiet, P., & Willis, R. J. (2021). Computerization, obsolescence and the length of working life. *Labour Economics*, 77(509): 102005. https://doi.org/10.1016/j.labeco.2021.102005

Hummels, D., Jørgensen, R., Munch, J., & Xiang, C. (2014). The wage effects of offshoring: Evidence from Danish matched worker-firm data. *American Economic Review*, *104*(6), 1597–1629. https://doi.org/10.1257/aer.104.6.1597

Hummels, D., Munch, J. R., & Xiang, C. (2018). Offshoring and labor markets. *Journal of Economic Literature*, *56*(3), 981–1028. https://doi.org/10.1257/jel.20161150

Kleinert, Corinna, and Oliver Wölfel. 2018. Technologischer Wandel Und Weiterbildungsteilnahme [Technological Change and Participation in Continuing Education]. BIBB Policy Biref 1/20, 2018.

Kokshagina, O. and Schneider, S. (2023) The digital workplace: navigating in a jungle of paradoxical tensions. *Californian Management Review*. 65(2), pp.129-155.

Levine, L. (2005). Offshoring (a.k.a. Offshore Outsourcing) and Job Insecurity Among U.S. Workers. *CRS Report for Congress*.

Levy, F., & Murnane, R. J. (2004). *The new division of labor: How computers are creating the next job market* (Princeton).

Li, L., Singleton, P. (2021). The effect of industrial robots on workplace safety. *Center for Policy Research 276.*

Lingmont, D. N. J., & Alexiou, A. (2020). The contingent effect of job automating technology awareness on perceived job insecurity: Exploring the moderating role of organizational culture. *Technological Forecasting and Social Change*, *161*, 120302. https://doi.org/10.1016/j.techfore.2020.120302

Martin, L. (2017). Do innovative work practices and use of information and communication technologies motivate employees? *Industrial Relations*, *56*(2), 263–292. https://doi.org/10.1111/irel.12173

Martin, L., & Hauret, L. (2022). Digitalization, job quality and subjective well-being. In K. F. Zimmermann (Ed.), *Handbook of Labor, Human Resources and Population Economics*. Springer Nature.

Martin, L., & Omrani, N. (2015). An assessment of trends in technology use, innovative work practices and employees' attitudes in Europe. *Applied Economics*, *47*(6), 623–638. https://doi.org/10.1080/00036846.2014.978072

Martin, L., Pénard, T., & Poussing, N. (2022). Are employees happier when staying connected with their companies outside working hours? *Social Science Computer Review* 40(4): 1035–1053.

McGuinness, S., Pouliakas, K., & Redmond, P. (2021). Skills-displacing technological change and its impact on jobs: challenging technological alarmism? *Economics of Innovation and New Technology*. https://doi.org/10.1080/10438599.2021.1919517

Melzer, S. M., & Diewald, M. (2020). How individual involvement with digitalized work and digitalization at the workplace level impacts supervisory and coworker bullying in German workplaces. *Social Sciences*, *9*(9). https://doi.org/10.3390/SOCSCI9090156

Michaels, G., Natraj, A., and Van Reenen, J. (2014). 'Has ICT polarized skill demand? Evidence from eleven countries over 25 years.' *Review of Economics and Statistics,* 96(1), 60– 77. https://doi.org/10.1162/REST_a_00366

Mihaylov, E., & Tijdens, K.G. (2019). Measuring the routine and non-routine task content of 427 four-digit ISCO-08 occupations. *Tinbergen Institute Discussion Paper 2019-035/V*

Nazareno, L. and Schiff, D. S. (2021). The impact of automation and artificial intelligence on worker well-being. *Technology in Society*, 67, *101679.* https://doi.org/10.1016/j.techsoc.2021.101679

Nikulin, D., Parteka, A., & Wolszczak-Derlacz, J. (2022). Working conditions in Europe: The role of global value chains and advanced digital production-driven technological specialisation. *European Trade Union Institute, Working Paper 2022.12*.

Nurski, L., & Hoffmann, M. (2022). Beating burnout: identifying bad jobs and improving job quality. *Policy Contribution 07/2022, Bruegel*.

Oswald, A. J., Proto, E., & Sgroi, D. (2015). Happiness and productivity. *Journal of Labour Economics*, *33*(4), 789–822. https://doi.org/10.1086/681096

Parteka, A., Wolszczak-Derlacz, J., & Nikulin, D. (2023). Digital technology, cross-border production links and employee well-being: evidence from Europe, *Mimeo.*

Pauliková, A., Babel'ová, Z.G. & Ubárová, M. (2021). Analysis of the impact of human–cobot collaborative manufacturing implementation on the occupational health and safety and the quality requirements. *International Journal of Environmental Research and Public Health* 18(4): 1–15. https://doi.org/10.3390/ijerph18041927

Sayah, S. (2013). Managing work-life boundaries with information and communication technologies: the case of independent contractors. *New Technology, Work and Employment*, *28*(3), 179–196. https://doi.org/10.1111/ntwe.12016

Schmidpeter, B., & Winter-Ebmer, R. (2018). How do automation and offshorability influence unemployment duration and subsequent job quality? *IZA Discussion Paper No 11736*.

Smith, A., & Anderson, J. (2014) AI, robotics, and the future of jobs. Pew Research Center, August 1–73.

So, B.C.L., Cheng, A.S.K., & Szeto, G.P.Y. (2017). Cumulative IT use is associated with psychosocial stress factors and musculoskeletal symptoms. *International Journal of Environmental Research and Public Health*, 14:1541. https://doi.org/10.3390/ijerph14121541

Tolan, S., Pesole A., Martinez-Plumed, F., Fernandez-Macias, E., Hernandez-Orallo, J. and Gomez, E. (2021). Measuring the occupational impact of AI: Tasks, cognitive abilities and AI benchmarks. *Journal of Artificial Intelligence Research 71*, 191-236. https://doi.org/10.1613/jair.1.12647

UNECE. (2015). Handbook on measuring quality of employment: A statistical framework. *United Nations Economic Commission for Europe Report*.

Wang, Z., Wei, S.-J., Yu, X., Zhu, K., & Wang, Z., Wei, S., Yu, X., & Zhu, K. (2017). Measures of participation in global value chains and global business cycles. *NBER Working Paper No. 23222*, Article NBER Work. Pap. No. 23222.

Warr, P. B. (1999). Well-being and the workplace. In D. Kahneman, E. Diener, & N. Schwarz (Eds.), *Well-being: The Foundations of Hedonic Psychology* (pp. 392–412). Russell Sage Foundation.

Wood, A. J., & Lehdonvirta, V. (2021). Antagonism beyond employment: how the 'subordinated agency' of labour platforms generates conflict in the remote gig economy. *Socio-Economic Review*, *19*(4), 1369–1396. https://doi.org/10.1093/ser/mwab016

Wood, S., van Veldhoven, M., Croon, M. A., & de Menezes, L. M. (2012). Enriched job design, high involvement management and organizational performance: The mediating roles of job satisfaction and well-being. *Human Relations*, *65*(4), 419–446. https://doi.org/10.1177/0018726711432476

Wright, K. B., Abendschein, B., Wombacher, K., O'Connor, M., Hoffman, M., Dempsey, M., Krull, C., Dewes, A., & Shelton, A. (2014). Work-related communication technology use outside of regular work hours and work life conflict: The influence of communication technologies on perceived work life conflict, burnout, job satisfaction, and turnover intentions. *Management Communication Quarterly*, *28*(4), 507–530. https://doi.org/10.1177/0893318914533332

Zelenski, J. M., Murphy, S. A., & Jenkins, D. A. (2008). The happy-productive worker thesis revisited. *Journal of Happiness Studies*, *9*(4), 521–537. https://doi.org/10.1007/s10902-008-9087-4

Annexes

Annex 1: Job quality indicators details

Safety at work

Category	Indicator	Sub-indicator	Question number (2015)	EWCS question (2015)	Data availability
Safety at work	Risks at work	Ergonomic risks	Q30a	Does your main paid job involve tiring or painful positions?	2005-2021
			Q30b	Does your main paid job involve lifting or moving people?	2005-2021
			Q30c	Does your main paid job involve carrying or moving heavy loads?	2005-2021
			Q30e	Does your main paid job involve repetitive hand or arm movements?	2005-2021
		Environmental risks	Q29b	Are you exposed at work to noise so loud that you would have to raise your voice to talk to people?	2005-2021
			Q29g	Are you exposed at work to handle or be in skin contact with chemical products or substances?	2005-2021
			Q29i	Are you exposed at work to handle or be in direct contact with materials which can be infectious, such as waste, bodily fluids, laboratory materials, etc.?	2005-2021
		Physical risks	Q78c	Over the last 12 months, did you have any backache?	2005-2021
			Q78d	Over the last 12 months, did you have muscular pains in shoulders, neck and/or upper limbs (arms, elbows, wrists, hands etc.)?	2005-2021

Fair treatment

Category	Indicator	Question number (2015)	EWCS question (2015)	Data availability
Fair treatment	Asocial behaviour	Q80a	Over the last month, during the course of your work have you been subjected to verbal abuse?	2010-2021
		Q80b	Over the last month, during the course of your work have you been subjected to unwanted sexual attention?	2010-2021
		Q81a	And over the past 12 months, during the course of your work have you been subjected to physical violence?	2005-2021

Working time and Work-life balance

Category	Indicator	Question number (2015)	EWCS question (2015)	Data availability
Working time and work-life balance	Work life balance in general	Q44	In general, how do your working hours fit in with your family or social commitments outside work?	2005-2021
	Work on high speed	Q49a	Does your job involve working at very high speed?	2005-2021
	Working time satisfaction		Difference between the preferred working hours per week and the effective working hours per week	2005-2021

Security of employment

Category	Indicator	Question number (2015)	EWCS question (2015)	Data availability
Security of employment	Job security	Q89g	I might lose my job in the next 6 months	2005-2021

Self-perceived fair pay

Category	Indicator	Question number (2015)	EWCS question (2015)	Data availability
Self-perceived fair pay	Self-perceived fair pay	Q89a	Considering all my efforts and achievements in my job, I feel I get paid appropriately	2005-2021

Social dialogue

Category	Indicator	Question number (2015)	EWCS question (2015)	Data availability
Social dialogue	Social dialogue	Q71a	Does the following exist at your company or organisation? Trade union, works council or a similar committee representing employees?	2015-2021
	Work on high speed	Q71b	Does the following exist at your company or organisation? Health and safety delegate or committee?	2015-2021
	Working time satisfaction	Q71c	Does the following exist at your company or organisation? A regular meeting in which employees can express their views about what is happening in the organisation	2015-2021

Skills development and training

Category	Indicator	Question number (2015)	EWCS question (2015)	Data availability
Skills development and training	Training	Q65a	Over the past 12 months, have you undergone training paid for or provided by your employer to improve your skills?	2005-2021
		Q65c	Over the past 12 months, have you undergone on-the-job training (by co-workers, supervisors) to improve your skills?	2005-2021
	Learning new things	Q53f	Generally, does your main paid job involve learning new things?	2005-2021

Employment-related relationships and work motivation

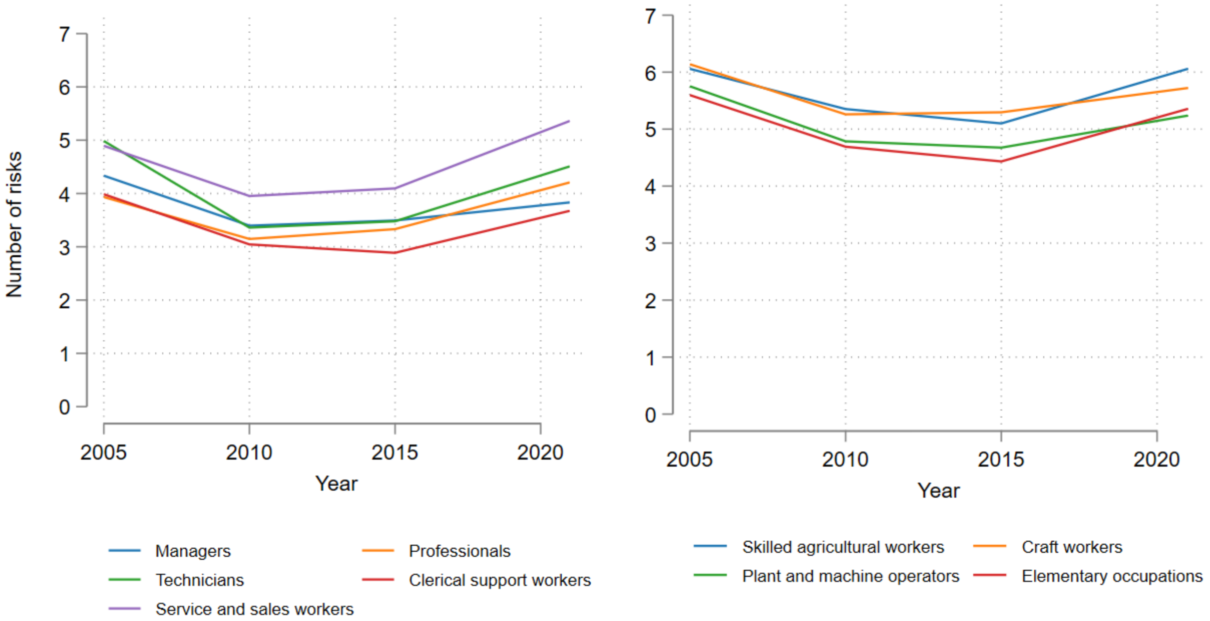
Category	Indicator	Question number (2015)	EWCS question (2015)	Data availability
Employment related relationships and work motivation	Autonomy at work	Q54a	Are you able to choose or change your order of tasks?	2005-2021
		Q54b	Are you able to choose or change your methods of work?	2005-2021
		Q54c	Are you able to choose or change your speed or rate of work?	2005-2021
	Support	Q61a	Your colleagues help and support you	2005-2021
		Q61b	Your manager helps and supports you	2005-2021
	Being consulted at work	Q61c	You are consulted before objectives are set for your work	2010-2021
		Q61d	You are involved in improving the work organisation or work processes of your department or organisation	2010-2021

Annex 2. Descriptive statistics

Variables	Obs	Mean	Std. dev.	Min	Max
Job quality					
Poor safety at work	10,617	0.55	0.50	0	1
Poor treatment at work	6,958	0.04	0.14	0	1
High speed	10,617	0.83	0.38	0	1
Work-life balance	10,594	3.09	0.82	1	4
Interference	10,617	0.34	0.47	0	1
Job insecurity	10,388	0.15	0.36	0	1
Fair wage	7,113	0.61	0.49	0	1
Social dialogue	5,392	0.65	0.35	0	1
Training paid by employer	7,133	0.52	0.50	0	1
Organisational support	10,617	0.98	0.12	0	1
Consulted at work	10,617	0.92	0.22	0	1
Work motivation	10,617	0.92	0.20	0	1
Technological change					
Advanced digital technologies	10,617	1.14	0.48	0.43	2.24
Automation	10,617	0.11	0.13	0.00	0.62
Artificial intelligence	10,617	0.62	0.27	0.03	0.99
Controls					
Gender					
Women	10,617	0.62	0.49	0	1
Men	10,617	0.38	0.49	0	1
Age					
16-34	10,617	0.34	0.47	0	1
35-54	10,617	0.52	0.50	0	1
55+	10,617	0.14	0.35	0	1
Education					
Secondary	10,585	0.40	0.49	0	1
Post-secondary	10,585	0.07	0.25	0	1
Tertiary	10,585	0.53	0.50	0	1
Part-time	10,617	0.85	0.36	0	1
Having children	10,617	0.37	0.48	0	1
Permanent contract	10,159	1.11	0.32	1	2
Task					
Nonroutine cognitive	10,617	0.46	0.50	0	1
Nonroutine manual	10,617	0.16	0.37	0	1
Routine cognitive	10,617	0.30	0.46	0	1
Routine manual	10,617	0.08	0.27	0	1
Firm size	10,617	1.75	0.84	1	3
Small	10,617	0.51	0.50	0	1
Medium	10,617	0.24	0.43	0	1
Large	10,617	0.25	0.44	0	1
Offshoring	8,397	0.09	0.28	0	1
Sector	10,617	2.67	1.22	1	4
Countries groups	10,617	2.51	0.97	1	4

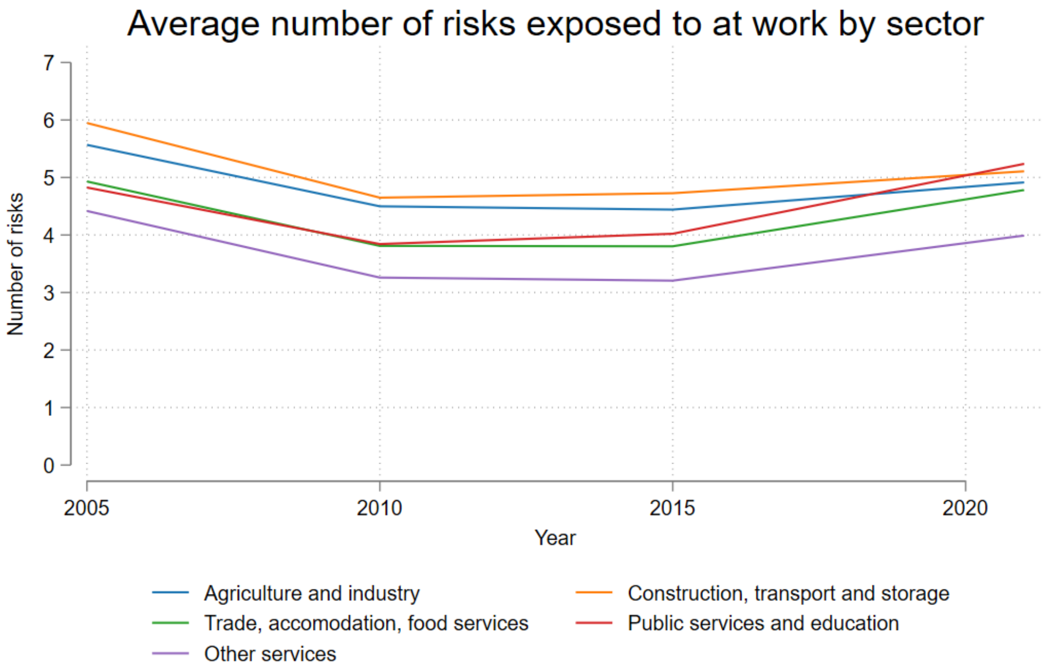
Annex 3. Safety at work

Figure a 1 Average number of risks exposed to at work by occupation



Note: Aggregated indicator based on Q30a, Q30b, Q30c, Q30e, Q29b, Q29g, Q29i, Q78c andQ78d, representing different types of risks at work. All the questions have been rescaled to binary indicators indicating if the person is exposed to the risk (0 No - 1 Yes). The average number of risks exposed to at work is the mean of the sum of these binary indicators. EWCS weighted data for all EU-27 countries.

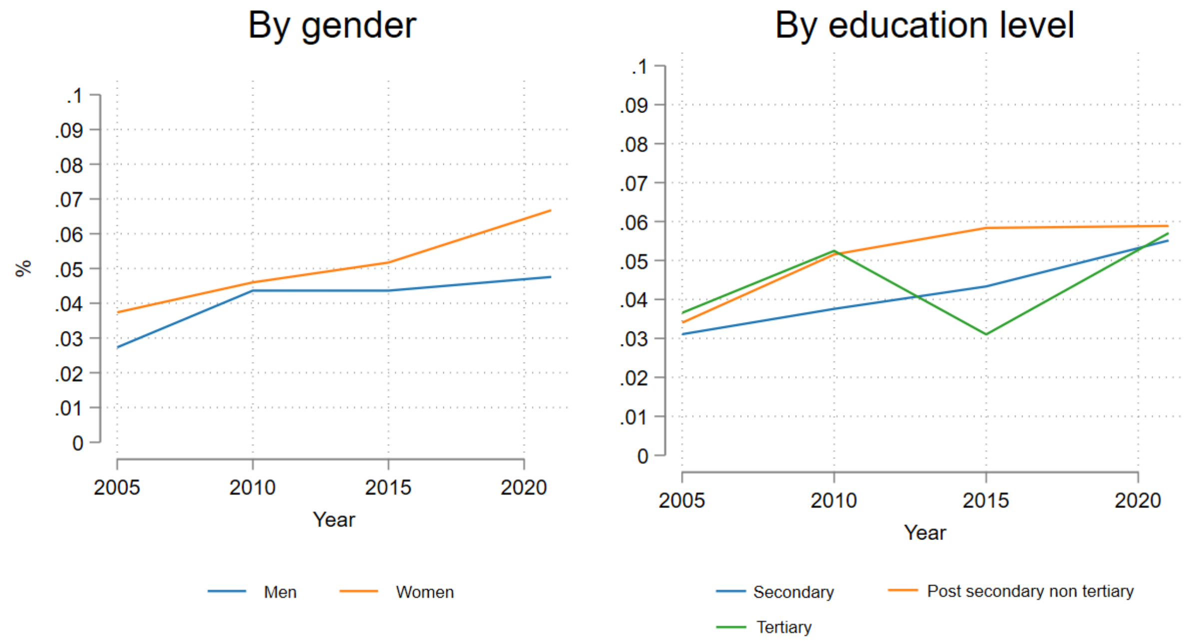
Figure a 2. Risks at work indicator by sector



Note: Aggregated indicator based on Q30a, Q30b, Q30c, Q30e, Q29b, Q29g, Q29i, Q78c andQ78d, representing different types of risks at work. All the questions have been rescaled to binary indicators indicating if the person is exposed to the risk (0 No - 1 Yes). The average number of risks exposed to at work is the mean of the sum of these binary indicators. EWCS weighted data for all EU-27 countries. NACE codes: Agriculture and industry = A='Agriculture'; B 'Mining and quarrying', C 'Manufacturing', D 'Electricity, gas, steam and air conditioning supply', E 'Water supply, sewerage, waste management and remediation activities', Construction, transport, storage = F ' Construction', H ' Transportation and storage', Trade, accommodation and food service activities = G ' Wholesale and retail trade, repair of motor vehicles and motorcycles', I 'Accommodation and food service activities', Public services and education = 0 'Public administration and defence', P 'Education', Q 'Human health and social work activities'; Other services = J 'Information and communication', K 'Financial and insurance activities', L 'Real estate activities', M 'Professional, scientific and technical activities', N 'Administrative and support service activities', R 'Arts, entertainment and recreation', S 'Other service activities', T 'Activities of households as employers', U 'Activities of extraterritorial organisations'.

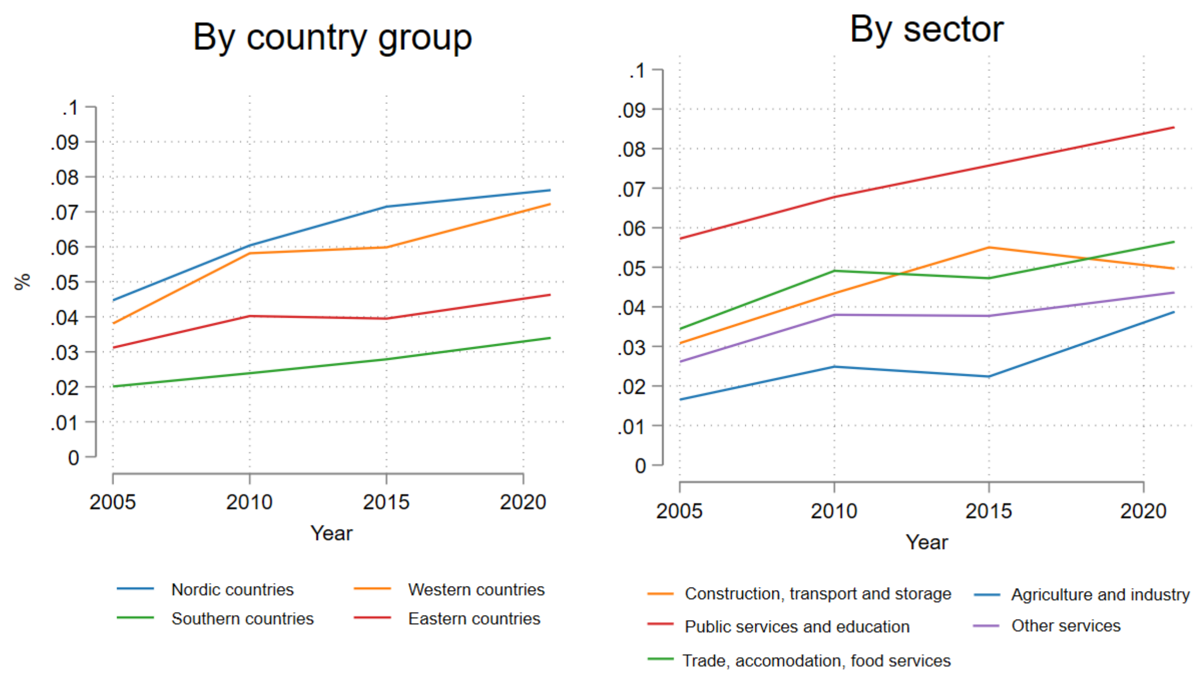
Annex 4. Fair treatment

Figure a 3 Share of persons exposed to asocial behaviours at work



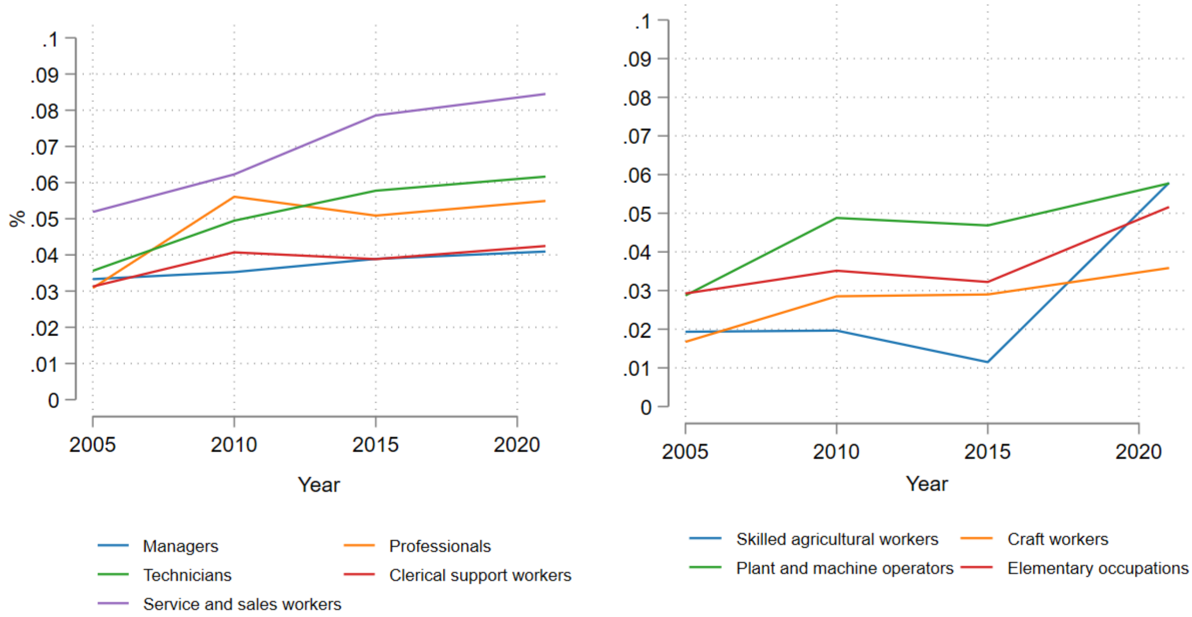
Note: Aggregated indicator based on Q80a, Q80b and Q81a, representing different types of asocial behaviour at work. All the questions have been rescaled to binary indicators indicating if the person is exposed to the asocial behaviour (0 No - 1 Yes). The share of persons exposed to at least one asocial behaviour at work is the share of observations for which the sum of these binary indicators is greater than 0. EWCS weighted data for all EU-27 countries.

Figure a 4 Share of persons exposed to asocial behaviours at work



Note: Aggregated indicator based on Q80a, Q80b and Q81a, representing different types of asocial behaviour at work. All the questions have been rescaled to binary indicators indicating if the person is exposed to the asocial behaviour (0 No - 1 Yes). The share of persons exposed to at least one asocial behaviour at work is the share of observations for which the sum of these binary indicators is greater than 0. EWCS weighted data for all EU-27 countries.

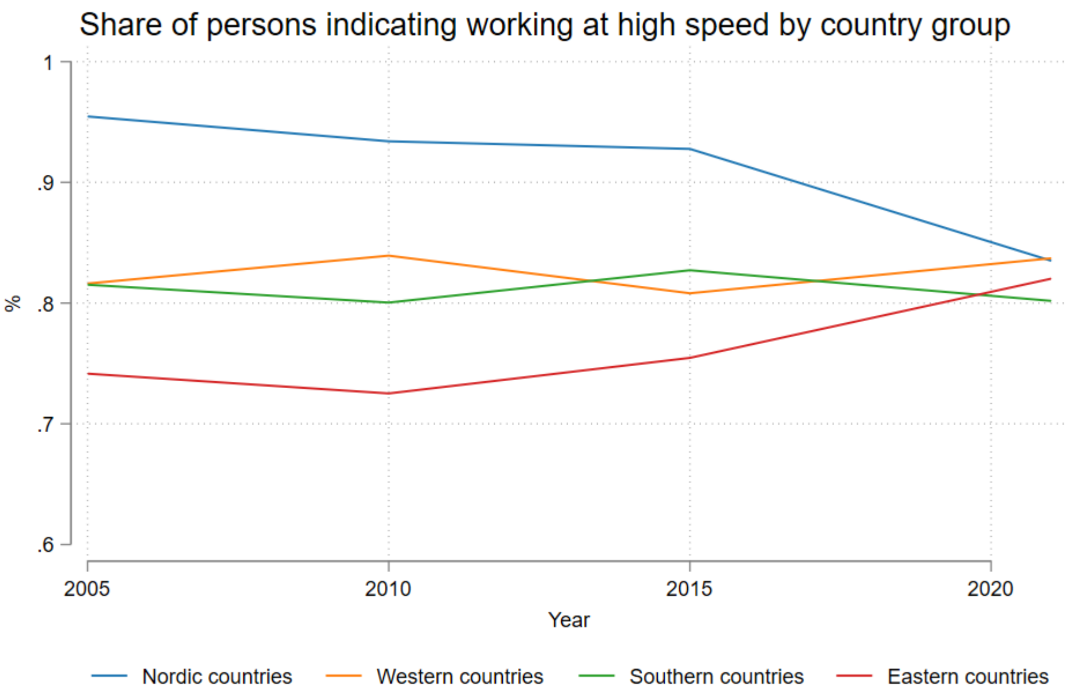
Figure a 5 Share of persons exposed to asocial behaviours at work by occupation



Note: Aggregated indicator based on Q80a, Q80b and Q81a, representing different types of asocial behaviour at work. All the questions have been rescaled to binary indicators indicating if the person is exposed to the asocial behaviour (0 No - 1 Yes). The share of persons exposed to at least one asocial behaviour at work is the share of observations for which the sum of these binary indicators is greater than 0. EWCS weighted data for all EU-27 countries.

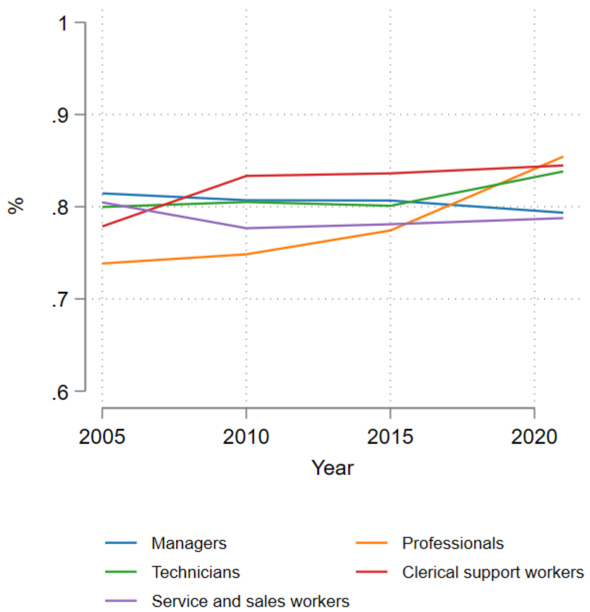
Annex 5. Working time and work life balance

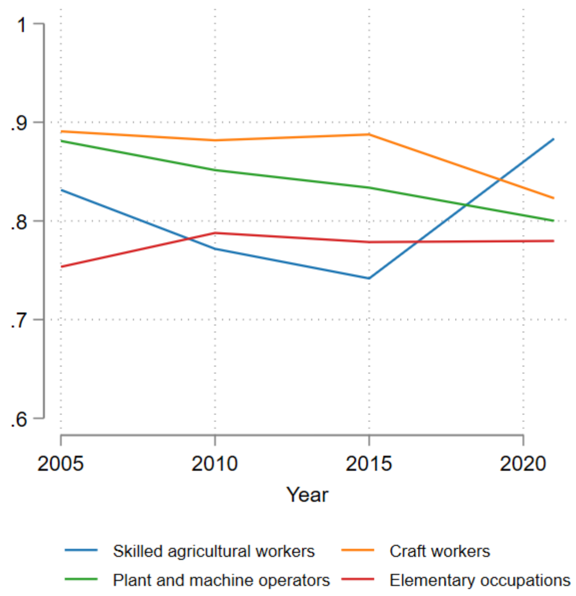
Figure a 6 Work at high speed by country group



Note: Question 40a: Does your job involve working at a very high speed? Rescaled to a binary indicator indicating if the person is working at high speed (0 No - 1 Yes). EWCS weighted data for all EU-27 countries.

Figure a 7 Work at high speed by occupation

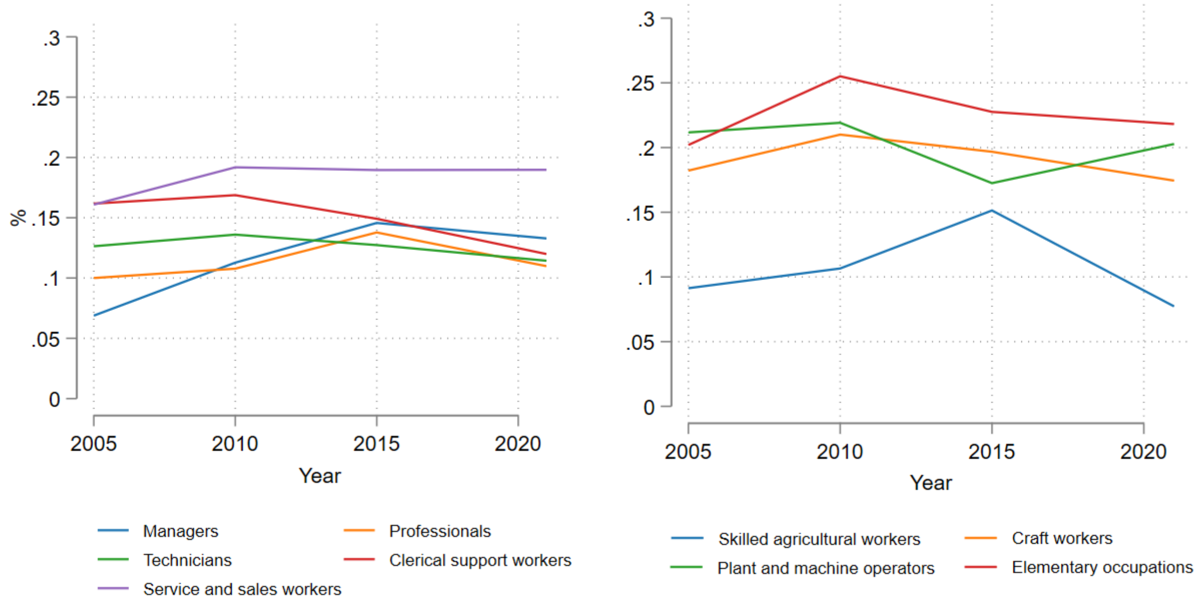




Note: Question 40a: Does your job involve working at a very high speed? Rescaled to a binary indicator indicating if the person is working at high speed (0 No - 1 Yes). EWCS weighted data for all EU-27 countries.

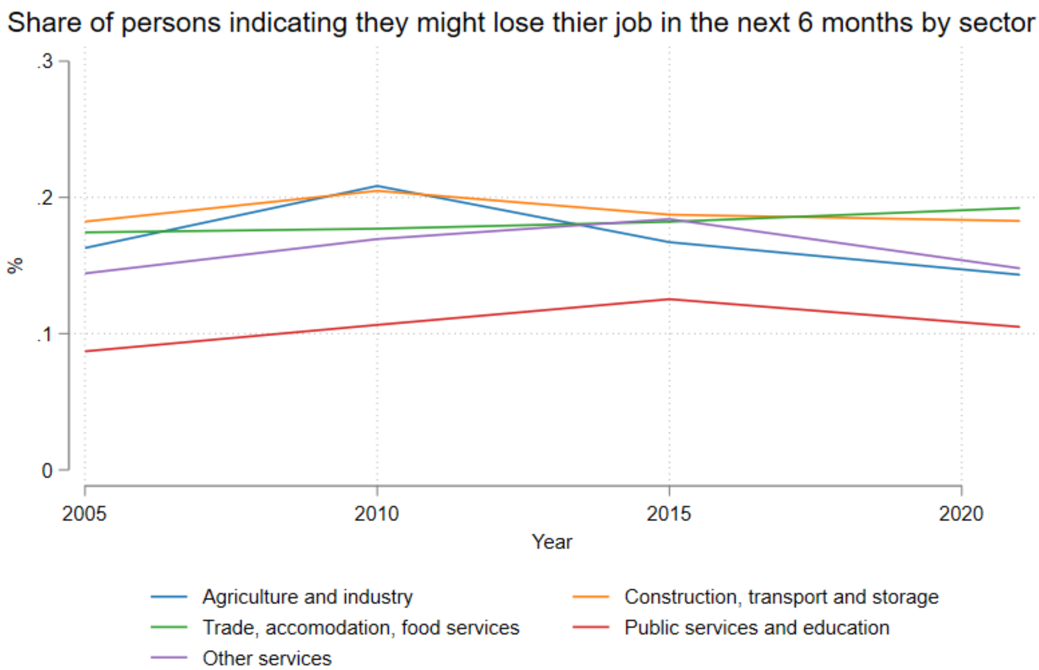
Annex 6. Security of employment

Figure a 8 Job insecurity by occupation



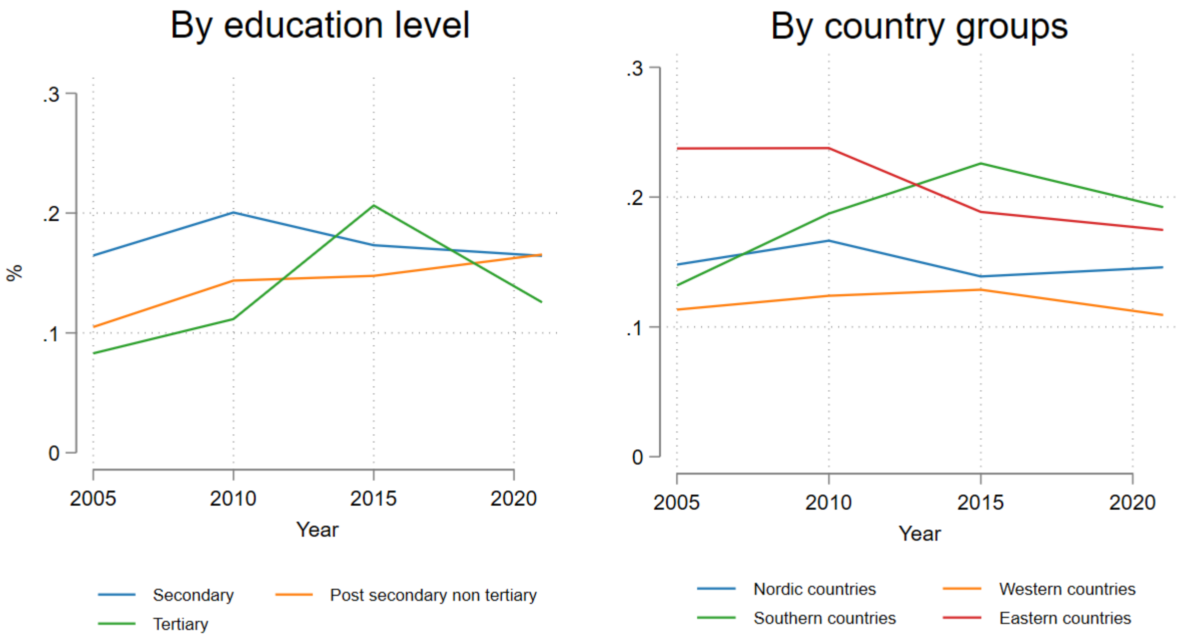
Note: Question 89g: I might lose my job in the next 6 months (0 Strongly disagree, tend to disagree and neither agree nor disagree - 1 Tend to agree and strongly agree). EWCS weighted data for all EU-27 countries.

Figure a 9 Job insecurity by sector



Note: Question 89g: I might lose my job in the next 6 months (0 Strongly disagree, tend to disagree and neither agree nor disagree - 1 Tend to agree and strongly agree). EWCS weighted data for all EU-27 countries. NACE codes: Agriculture and industry = A=‘Agriculture’; B ‘Mining and quarrying’, C ‘Manufacturing’, D ‘Electricity, gas, steam and air conditioning supply’, E ‘Water supply, sewerage, waste management and remediation activities’, Construction, transport, storage = F ‘ Construction’, H ‘ Transportation and storage’, Trade, accommodation and food service activities = G ‘ Wholesale and retail trade, repair of motor vehicles and motorcycles’, I ‘Accommodation and food service activities’, Public services and education = 0 ‘Public administration and defence’, P ‘Education’, Q ‘Human health and social work activities’; Other services = J ‘Information and communication’, K ‘Financial and insurance activities’, L ‘Real estate activities’, M ‘Professional, scientific and technical activities’, N ‘Administrative and support service activities’, R ‘Arts, entertainment and recreation’, S ‘Other service activities’, T ‘Activities of households as employers’, U ‘Activities of extraterritorial organisations’.

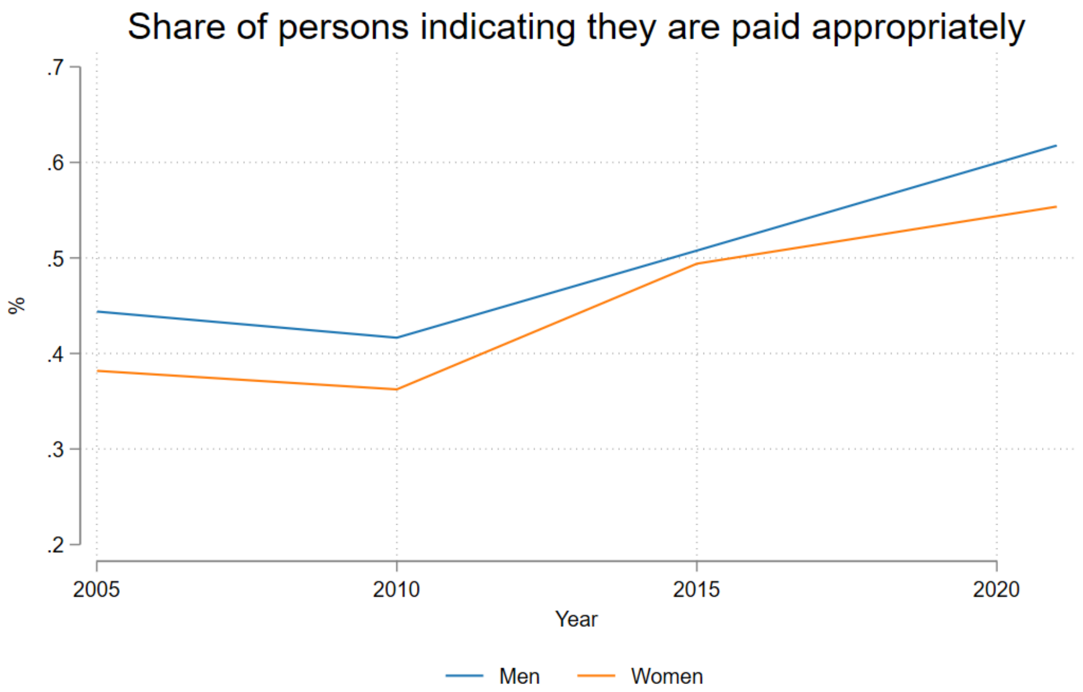
Figure a 10 Job insecurity



Note: Question 89g: I might lose my job in the next 6 months (0 Strongly disagree, tend to disagree and neither agree nor disagree - 1 Tend to agree and strongly agree). EWCS weighted data for all EU-27 countries.

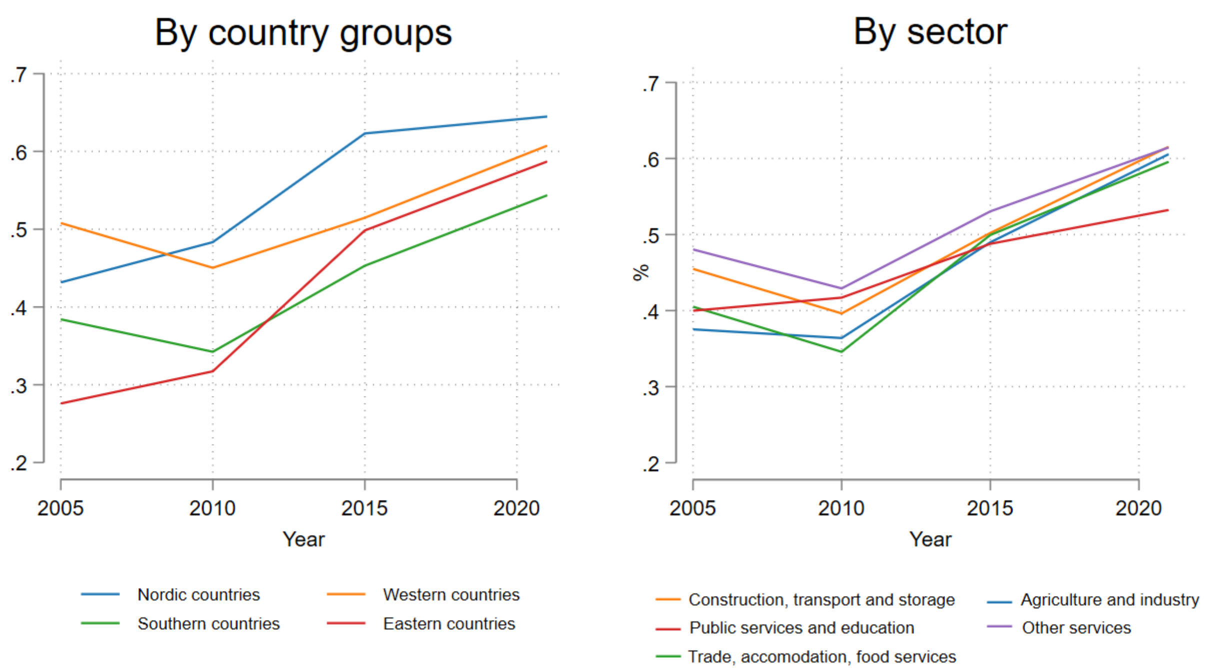
Annex 7. Self-perceived fair pay

Figure a 11 The feeling of being paid appropriately by gender



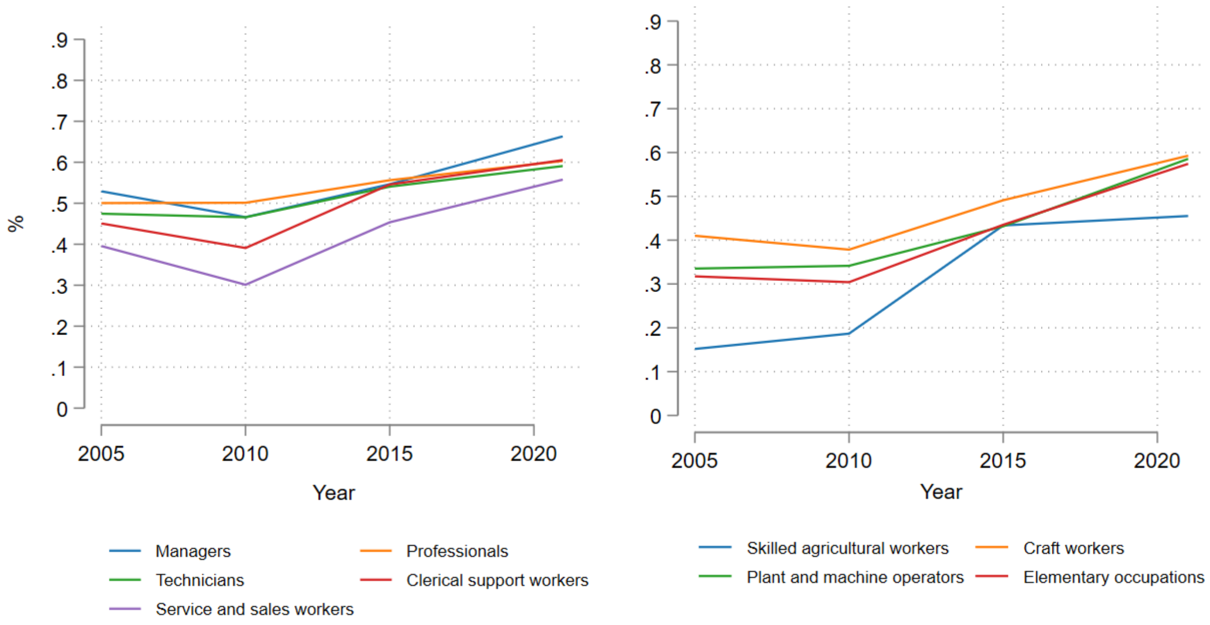
Note: Question 89a: Considering all my efforts and achievements in my job, I feel I get paid appropriately (0 Strongly disagree, tend to disagree and neither agree nor disagree - 1 Tend to agree and strongly agree). EWCS weighted data for all EU-27 countries.

Figure a 12 The feeling of being paid appropriately



Note: Question 89a: Considering all my efforts and achievements in my job, I feel I get paid appropriately (0 Strongly disagree, tend to disagree and neither agree nor disagree - 1 Tend to agree and strongly agree). EWCS weighted data for all EU-27 countries.

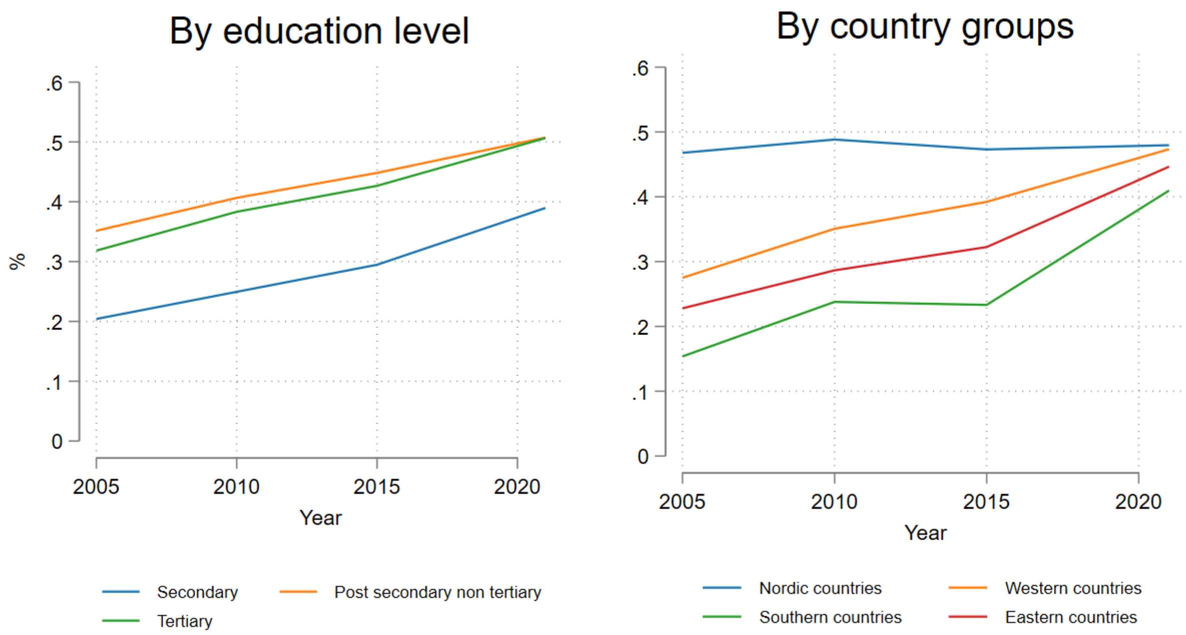
Figure a 13 The feeling of being paid appropriately by occupation



Note: Question 89a: Considering all my efforts and achievements in my job, I feel I get paid appropriately (0 Strongly disagree, tend to disagree and neither agree nor disagree - 1 Tend to agree and strongly agree). EWCS weighted data for all EU-27 countries.

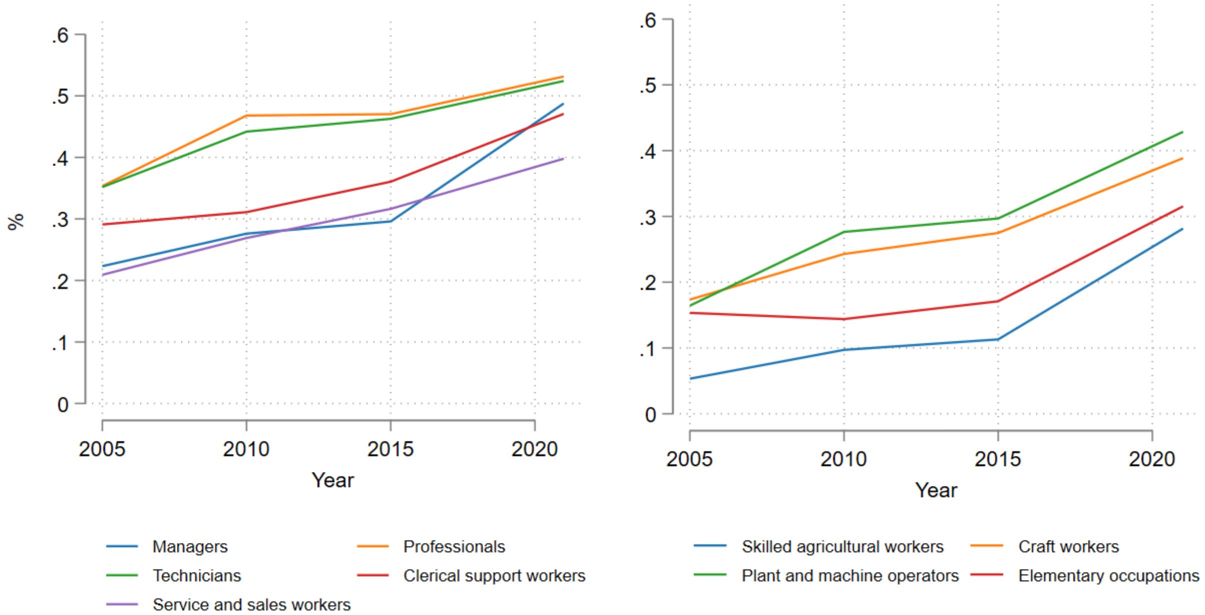
Annex 8. Skills development and training

Figure a 14 Share of persons having undergone training



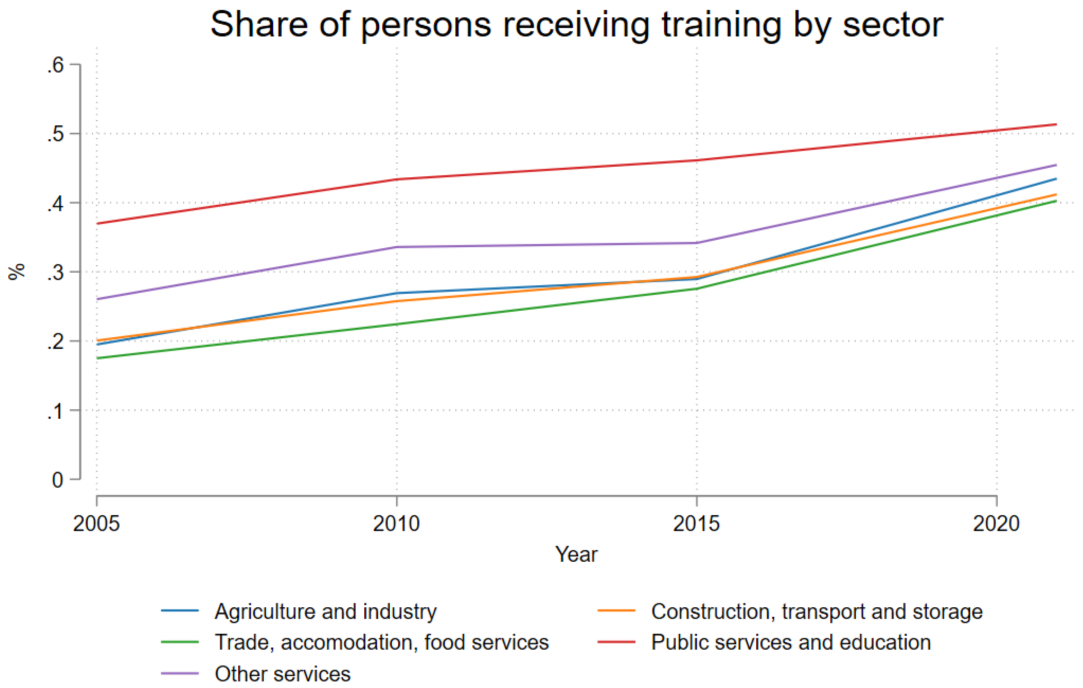
Note: Aggregated indicator based on Q65a, Q65c, representing different options of training (paid by the employer or on the job). These questions have been rescaled to binary indicators indicating if the person has undergone such training (0 No - 1 Yes). The share of persons having undergone training is the share of observations for which the sum of these binary indicators is greater than 0. EWCS weighted data for all EU-27 countries.

Figure a 15 Share of persons having undergone training by occupation



Note: Aggregated indicator based on Q65a, Q65c, representing different options of training (paid by the employer or on the job). These questions have been rescaled to binary indicators indicating if the person has undergone such training (0 No - 1 Yes).. The share of persons having undergone training is the share of observations for which the sum of these binary indicators is greater than 0. EWCS weighted data for all EU-27 countries.

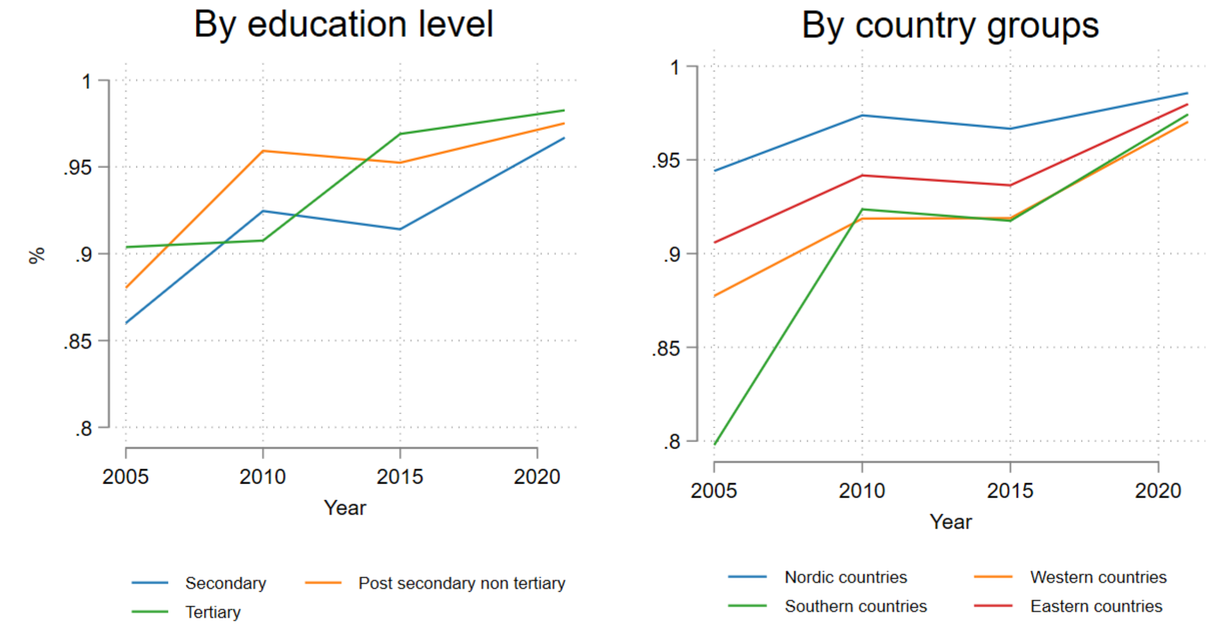
Figure a 16 Share of persons having undergone training by sector



Note: Aggregated indicator based on Q65a, Q65c, representing different options of training (paid by the employer or on the job). These questions have been rescaled to binary indicators indicating if the person has undergone such training (0 No – 1 Yes). The share of persons having undergone training is the share of observations for which the sum of these binary indicators is greater than 0. EWCS weighted data for all EU-27 countries. NACE codes: Agriculture and industry = A ='Agriculture'; B 'Mining and quarrying', C 'Manufacturing', D 'Electricity, gas, steam and air conditioning supply', E 'Water supply, sewerage, waste management and remediation activities', Construction, transport, storage = F ' Construction', H ' Transportation and storage', Trade, accommodation and food service activities = G ' Wholesale and retail trade, repair of motor vehicles and motorcycles', I 'Accommodation and food service activities', Public services and education = 0 'Public administration and defence', P 'Education', Q 'Human health and social work activities'; Other services = J 'Information and communication', K 'Financial and insurance activities', L 'Real estate activities', M 'Professional, scientific and technical activities', N 'Administrative and support service activities', R 'Arts, entertainment and recreation', S 'Other service activities', T 'Activities of households as employers', U 'Activities of extraterritorial organisations'.

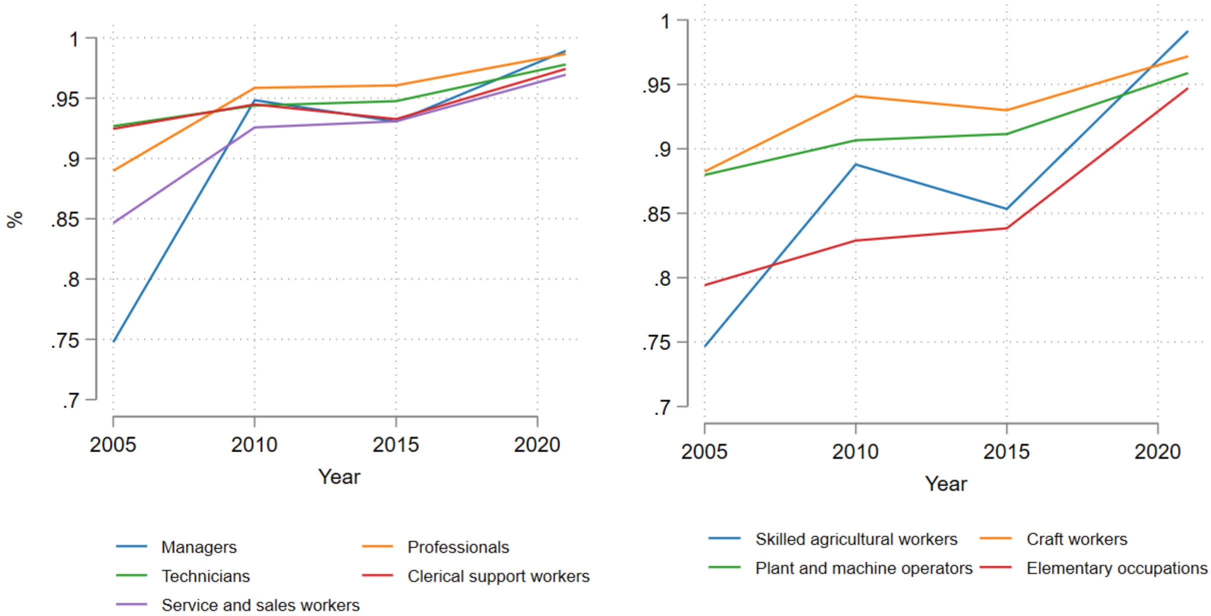
Annex 9. Employment-related relationships and work motivation

Figure a 17 Support at work



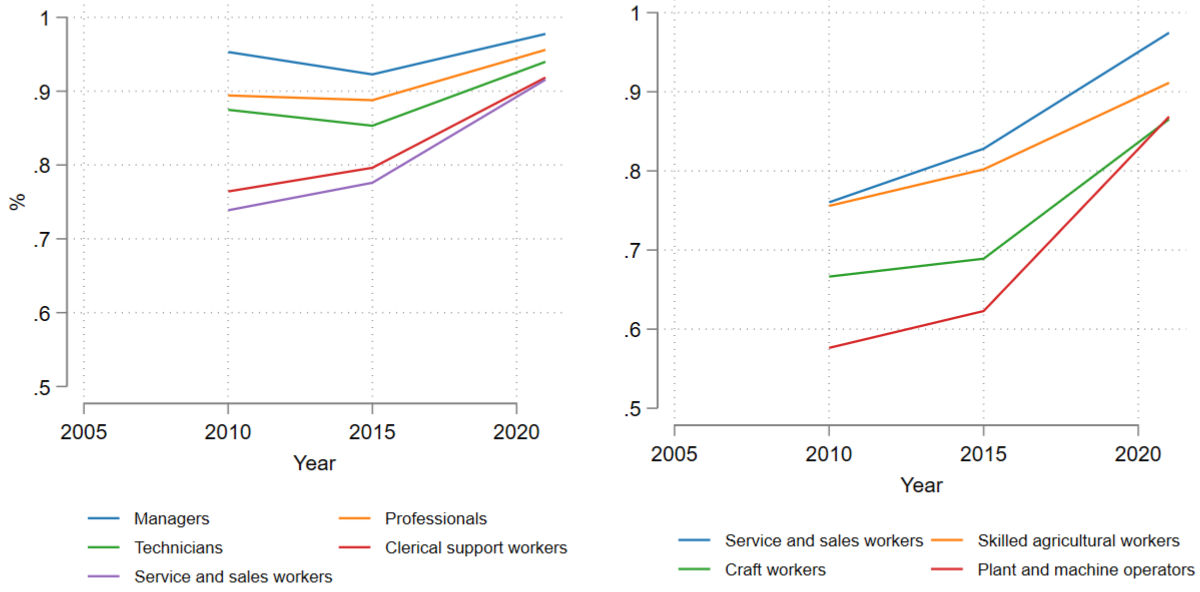
Note: Aggregated indicator based on Q61a and Q61b, representing different types of support at work (from the colleagues or the manager). All the questions have been rescaled to binary indicators indicating if the person receives such support (0 No - 1 Yes). The share of persons indicating they have support at work is the share of observations for which the sum of these binary indicators is greater than 0. EWCS weighted data for all EU-27 countries.

Figure a 18 Support at work by occupation



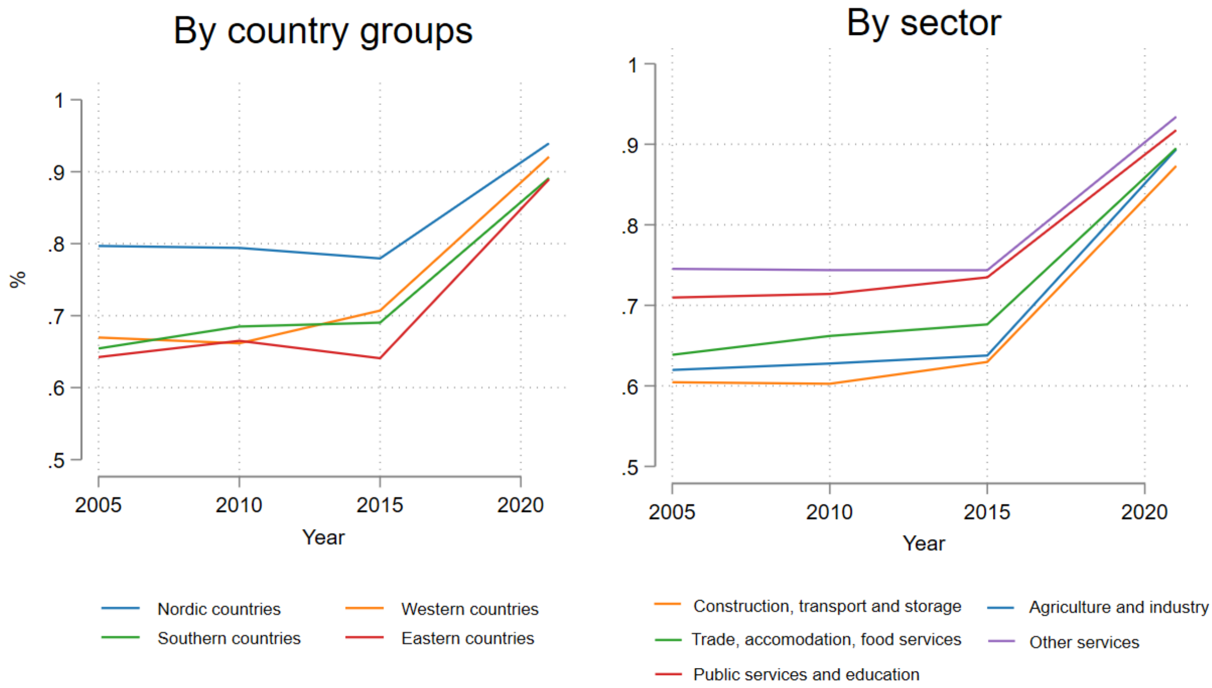
Note: Aggregated indicator based on Q61a and Q61b, representing different types of support at work (from the colleagues or the manager). All the questions have been rescaled to binary indicators indicating if the person receives such support (0 No - 1 Yes). The share of persons indicating they have support at work is the share of observations for which the sum of these binary indicators is greater than 0. EWCS weighted data for all EU-27 countries.

Figure a 19 Consulted at work by occupation



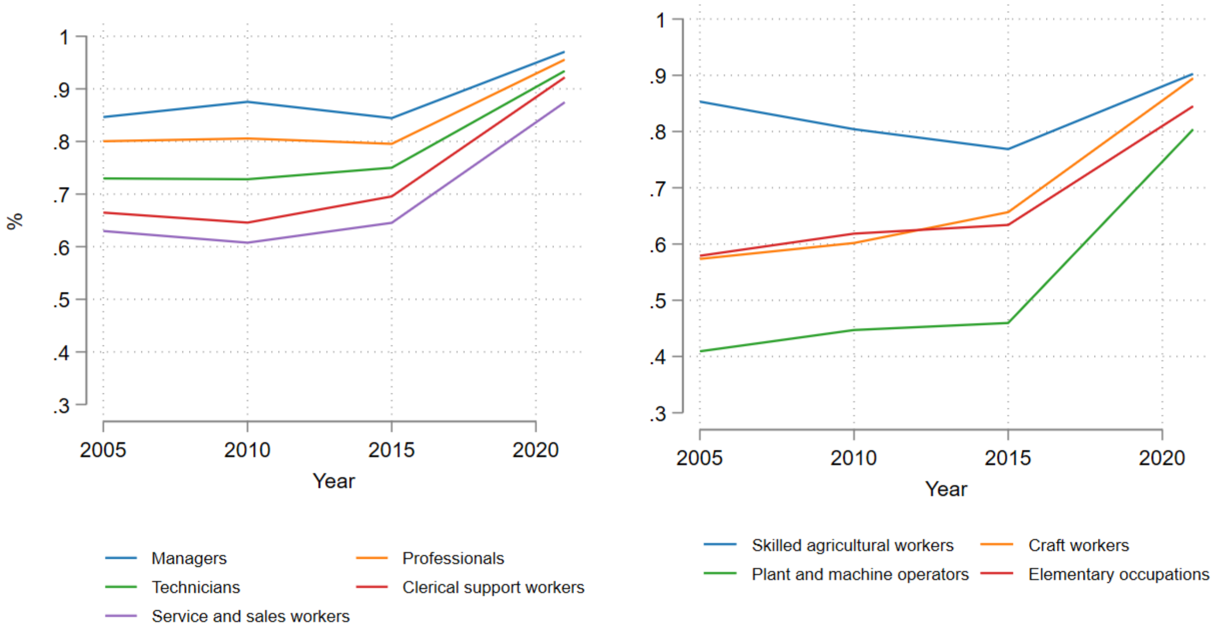
Note: Aggregated indicator based on Q61c and Q61d, representing different types of consultations at work. All the questions have been rescaled to binary indicators indicating if the person is being consulted (0 No - 1 Yes). The share of persons indicating they are being consulted at work is the share of observations for which the sum of these binary indicators is greater than 0. EWCS weighted data for all EU-27 countries.

Figure a 20 Share of persons reporting autonomy at work



Note: Aggregated indicator based on Q54a, Q54b and Q54c, representing different types of autonomy at work. All the questions have been rescaled to binary indicators indicating if the person has autonomy (0 No - 1 Yes). The share of persons indicating they have some autonomy at work is the share of observations for which the sum of these binary indicators is greater than 0. EWCS weighted data for all EU-27 countries. NACE codes: Agriculture and industry = A='Agriculture'; B 'Mining and quarrying', C 'Manufacturing', D 'Electricity, gas, steam and air conditioning supply', E 'Water supply, sewerage, waste management and remediation activities', Construction, transport, storage = F ' Construction', H ' Transportation and storage', Trade, accommodation and food service activities = G ' Wholesale and retail trade, repair of motor vehicles and motorcycles', I 'Accommodation and food service activities', Public services and education = 0 'Public administration and defence', P 'Education', Q 'Human health and social work activities'; Other services = J 'Information and communication', K 'Financial and insurance activities', L 'Real estate activities', M 'Professional, scientific and technical activities', N 'Administrative and support service activities', R 'Arts, entertainment and recreation', S 'Other service activities', T 'Activities of households as employers', U 'Activities of extra-territorial organisations'.

Figure a 21 Autonomy at indicator by occupation



Note: Aggregated indicator based on Q54a, Q54b and Q54c, representing different types of autonomy at work. All the questions have been rescaled to binary indicators indicating if the person has autonomy (0 No - 1 Yes). The share of persons indicating they have some autonomy at work is the share of observations for which the sum of these binary indicators is greater than 0. EWCS weighted data for all EU-27 countries.

Annex 10: Relationships between dimensions of job quality and digital transformation

	ADT	Automation	AI
Poor safety at work	-**	*Not significant (ns.)*	*ns.*
Poor treatment at work	+*	+***	-***
Working time satisfaction	*ns.*	*ns.*	+**
High speed at work	+**	-***	+***
Work life balance	*ns.*	-***	+***
Job insecurity	*ns.*	*ns.*	-**
Self-perceived fair paid	+*	*ns.*	*ns.*
Training paid by employer	+**	*ns.*	+***
Autonomy	+**	-***	+***
Organisational support	*ns.*	-**	+***
Consulted at work	*ns.*	-***	+***

UNTANGLED Partners:

UNTANGLED is a three-year interdisciplinary Horizon 2020 research project that seeks to examine the interconnected trends of globalisation, demographic change and technological transformation, and their effects on labour markets in the European Union and beyond. By engaging a broad range of stakeholders, including companies and civil society organisations, we will develop practical policy proposals to help governments cushion the negative impacts of these trends and ensure their benefits are enjoyed fairly across regions and sectors.