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Abstract

This paper's analysis of working conditions in Europe compares several aspects of job quality and wages, rather than relying on earnings as a sole indicator of workers' well-being. We use a micro-level database of workers from 22 European countries to assess how global value chains (GVCs) and advanced digital production (ADP) technologies affect working conditions. We show that the estimated link between GVC involvement and working conditions is conditional on the technological content of the job: the two aspects should not be analysed separately. The exact effect varies across types of technological exposures and particular aspects of job quality. In occupations of high software and robot exposure, job quality tends to deteriorate as GVC involvement increases. This effect is largely negligible for monetary wages. However, we argue that wages for low software, robot and AI-exposed occupations decrease with GVC intensity.

Keywords: working conditions, global value chains (GVCs), advanced digital production (ADP) technological specialisation

JEL: F1, F6, J8, O33

1. Introduction

This paper assesses the relationship between the working conditions of European employees and two major global trends: production fragmentation across borders (reflected in the involvement in global value chains (GVCs)), and technological progress driven by advanced digital production (ADP) technologies[1]. Working conditions constitute an important part of social life, as reflected in international policy measures and strategies such as the United Nations 2030 Sustainable Development Goals (SDGs). The struggle to ensure decent work standards is not restricted to the developing world and problems such as hazardous conditions or child labour (Delautre et al. 2021). Job quality is a challenge in well-developed areas like Europe, too. The Treaty on the Functioning of the European Union (TFEU), the Lisbon Strategy and the Europe 2020 Strategy all indicate that improving labour rights is one of the main targets for European labour markets. The current EU's 2030 Agenda, addressing the UN's SDGs, 'calls for providing opportunities for full and productive employment and decent work for all' (Goal 8)[2].

Nonetheless, the quality of working life still differs widely across Europe, depending on the sex, age, contractual status and occupation of workers (Eurofound 2021). Worldwide changes driven by globalisation, digitalisation or demographic shifts have created a heterogeneity of working conditions across industries and jobs (Eurofound 2020). What is more, working conditions in Europe are not only diversified, but also - at least in some respects - unsatisfactory. For instance, Eurofound's 2015 European Working Conditions Survey (EWCS) (Eurofound 2017)[3] reports that about 40 per cent of workers employed in the commerce and hospitality sector work at high speed for at least three quarters of their working time, while 32 per cent of overall workers report long working days. Moreover, 'the reality of the changing workplace' results in the growth of psychosocial risk, work intensity and the blurred boundaries between work and non-work life (Eurofound 2021).

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1. In line with UNIDO 2020 Industrial Development Report, we view ADP technologies as 'technologies that combine hardware (advanced robots and 3D printers), software (big data analytics, cloud computing and artificial intelligence) and connectivity (the Internet of Things)' - see UNIDO (2019), main report: xvi.
2. https://ec.europa.eu/eurostat/web/sdi/decent-work-and-economic-growth [assessed 21 March 2022].
3. https://www.eurofound.europa.eu/surveys/european-working-conditions-surveys-ewcs. Fieldwork for EWCS 2020/2021 was halted due to COVID-19, and micro data is planned to be published in December 2022, so we are forced to rely on the previous survey (EWCS 2015).

There are many determinants of working standards, including the growth of temporary employment (Aleksynska 2018), within-firms' characteristics of employment structure (Clark et al. 2021), the use (and abuse) of technologies (Salanova et al. 2014; Badri et al. 2018; Brynjolfsson et al. 2018) and the complexity of value chains (Berliner et al. 2015; Bernhardt and Pollak 2016; Nikulin et al. 2021). We focus on the complex interplay between the latter two determinants: technological progress and GVCs. According to the 2020 World Development Report, about half of global trade takes place within GVCs (World Bank 2020). Intense production for GVCs has raised new concerns about working conditions and the protection of workers' rights (Delautre et al. 2021). Yet GVC-focused research has rarely dealt with such aspects of work as health and occupational safety, job satisfaction or job security (Budría and Milgram Baleix 2020; Geishecker 2012). Even if the social consequences of GVCs are analysed, they are mainly quantified in terms of their impact on wages or risk of job displacement (Baumgarten et al. 2013; Ebenstein et al. 2014; Geishecker et al. 2010; Parteka and Wolszczak-Derlacz 2019, 2020; Shen and Silva 2018; Hummels et al. 2018). They do not capture the full complexity of working standards, including less quantifiable aspects such as the quality of the physical environment at work, social support and management quality, career development prospects, work-life balance and the impact of work intensity on health and well-being (Eurofound 2021). We are aware that changes in business models due to cross-border production fragmentation within GVCs cannot be isolated from another powerful force of recent decades: the extremely rapid technological progress. Indeed, technology has fuelled the intensification of cross-border production links and the 'second unbundling' (Baldwin 2013). Given the exponential progress in ADP technologies (Aghion et al. 2019; Hernandez and Brown 2020), social scientists seem to be several steps behind the actual advancements in the digital sphere. While there is rich evidence about the effects of ICT or automation on workers performing routine tasks (for example, Autor et al. 2003; Autor and Handel 2013; Autor and Dorn 2013; Frey and Osborne 2017; Goos et al. 2014; Marcolin et al. 2016; Spitz-Oene 2006; Acemoglu and Restrepo 2020), the first studies on worker-level exposure to artificial intelligence (AI) have only just started to emerge (Brynjolfsson et al. 2018; Felten et al. 2019; Webb 2020).

The reading of the related literature (see Section 2) allows us to identify several specific research gaps to be addressed in our Europe-focused study. First, the effects of technology and GVCs on workers are rarely assessed beyond a purely economic perspective (wages and employment). Second, job quality-focused studies do not assess the role of production fragmentation in the context of the dynamically changing technological landscape, as embedded in GVCs. Third, we lack a broad cross-country view on working conditions in Europe that confronts the role of these two forces. We contribute by confronting the role of GVCs with technological specialisation of occupations driven by three distinct features of Industry 4.0: computerisation, automation and AI. We investigate the multifaceted nature of working conditions by providing estimates using monetary information (wage data) and information on different aspects of job quality. Our key underlying assumption is that non-wage job dimensions affect employees in a way that, in terms of impact on their well-being, is equally as important as wages. Such an approach is in line with the concept of equivalent income used in well-being literature (see, for example, Decancq et al. 2015 or Fleurbaey 2015) or the demand-control theory (Karasek and Theorell 1990) linking job demand and job strain with mental and physical condition of workers. One may postulate that bad extra-wage working conditions are compensated by higher salary, but the empirical evidence is rather weak here (see, for example, Bonhomme and Jolivet 2009; Fernandez and Nordman 2009).

In Section 2 we review the literature related to the determinants of working conditions. Section 3 documents some descriptive evidence on working conditions in Europe. In Section 4 we show our key results, linking observed trends in job quality and wages with GVC and technological features of jobs. Technical details of our analysis and full econometric estimates are described in detail in the appendices. Section 5 concludes.

2. The determinants of working conditions - a literature review

The literature on working conditions is extensive. In general, high job quality may be related to high pay, job security and development opportunities that in turn will be reflected in good employee well-being. The subjectivist approach assumes that individual well-being may be based on work preferences and perceived fulfilment (Holman 2013). Gaucher and Veenhoven (2021) show that workers' perceived job quality is hard to measure and requires the use of various notions of the perceived work-life quality of workers.

The existing literature on the determinants of workers' well-being is predominantly based on case studies and describes the quality of work for separate occupations or groups of workers. Factors at play may be either personal (features describing the situation of individuals, such as their occupation, supervisory responsibilities, level of autonomy, working hours or social context of work) or external, such as country-specific institutional and labour market context. Pichler & Wallace (2009) find that in the case of European workers, individual features of work such as occupation, type of contract, job-related training and subjective evaluations of extrinsic and intrinsic job characteristics are the most significant in explaining differences in job satisfaction. At the same time, they argue that cross-country differences are less important.

Empirical studies address a wide set of factors determining the well-being of workers. As there is no unique definition of working conditions and/or job quality (Clark 2015; Steffgen et al. 2020), multidimensional workers' well-being may be analysed from different perspectives, implicating alternative methodological approaches. We can quantify economic aspects of job quality using monetary indicators (such as wages), combined with proxies related to work intensity (working hours) or the type of work (evening/night/shift/temporary) (for example, Aleksynska 2018; Piasna 2018; Rossi 2013). However, other, non-monetary, features, reflected in such intrinsic aspects of work as autonomy, social utility and social relations, constitute critical features of workers' well-being (Mira 2021). The social context of jobs (Clark et al. 2021) and job preferences (Gallie et al. 2012) play an important role in overall job quality. Clark et al. (2009) suggests that job satisfaction may be related to the co-worker's wage, where the association may be both positive, as higher co-workers' wages may provide information about prospects (Clark et al. 2009; Javdani and Krauth 2020), but also negative if the worker's wage is below the median wage (Card et al. 2012). Another study of Clark et al. (2021) suggests that job position gender diversity is related to the higher workers' well-being. There are also important differences in how the different genders perceive aspects of a 'good job' (Kaufman and White 2015). Furthermore, job-attribute preferences reflecting the desire for specific work-related outcomes may also be diversified across other workers' characteristics, such as domestic circumstances, highest qualification held, and occupation (Sutherland 2012).

The related economic literature has attempted to quantify the implications of external global economic changes, such as production fragmentation across borders and technological progress. Vertical specialisation, first quantified via offshoring indicators (Baumgarten et al. 2013; Ebenstein et al. 2014; Egger et al. 2015) and recently measured in terms of involvement in GVC relying on input-output data (Feenstra and Sasahara 2018; Parteka and Wolszczak-Derlacz 2019, 2020), has been shown to have profound implications for the labour markets. The literature is abundant, but many studies have assessed the phenomena in a purely economic way, using information on wages (Baumgarten et al. 2013; Ebenstein et al. 2014; Geishecker et al. 2010; Parteka and Wolszczak-Derlacz 2019, 2020; Shen and Silva 2018)[4]. The use of wages as an indicator of working conditions can be partially justified by the concept of social upgrading[5]. This reflects the improvement in workers' well-being induced by the involvement in global production fragmentation processes (Milberg and Winkle 2011). According to the neoclassical theory, social upgrading and economic upgrading[6] should go hand in hand. Assuming that economic upgrading consists of an increase in productivity and that wage gains are a proxy for social upgrading, then, according to marginalist economics, an increase in marginal labour productivity will be associated with higher wages (Milberg and Winkler 2011).

However, the empirical literature on broadly understood social consequences of trade and the proliferation of GVCs that goes beyond wages gives contrasting results. Some empirical studies confirm a positive relationship, showing improvement in labour standards in companies that are more involved in international trade activities (Nadvi et al. 2004; Bair and Gereffi 2001). Another strand of research finds that the link between economic and social upgrading is industry specific (Bernhardt and Pollak 2016). Finally, some authors claim that greater GVC involvement may not produce better pay or working conditions (Gimet et al. 2015; Lee and Gereffi 2013; Lee et al. 2016).

4. A large body of related research deals with the effects of production fragmentation on employment and job displacement (Autor et al. 2014; Egger et al. 2015; Hummels et al. 2018) or labour market polarisation (Cirillo 2018; David and Dorn 2013, Goos et al. 2014).

5. Social upgrading may be defined as 'the process of improvement in the rights and entitlements of workers as social actors, which enhances the quality of their employment' (Barrientos et al. 2011: 324).

6. Economic upgrading may be divided into four dimensions: process, product, functional, and chain upgrading (for more details see Barrientos et al. 2011). In general, economic upgrading covers processes that foster innovation and competitiveness, and may be defined as the capacity of firms 'to make better products, to make products more efficiently, or to move into more skilled activities' (Pietrobelli and Rabelloti 2006:1).

The linkages between GVC and non-monetary aspects of working conditions have been mainly analysed from the perspective of the developing countries. These address such issues as: working hours, wages and overtime, hiring and contract practices, health and safety conditions (Lee et al. 2016); employment status, maternity benefits, paid leave, accommodation, medical care, and overtime pay (Kabeer and Mahmud 2004); work opportunities, measurable labour standards and enabling rights (Barrientos et al. 2015); safety, exploitation of workers, compliance with local labour laws, and sanitary conditions at the workplace (Bair and Gereffi 2001); and work environment, overtime, employment and social security, and enabling rights (Rossi 2013). The question of how job quality varies among different groups of workers in developed countries is rarely raised in relation to GVC. Existing evidence is often country and industry specific. For instance, Smith and Pickles (2015) find that in the Slovak clothing industry, wages and benefits in export-oriented companies may be higher, but employment stability is lower. In turn, Lloyd and James (2008) report the positive impact of GVCs on the health and safety of workers employed in the UK food processing industry. Budría and Milgram Baleix (2020) investigate the effects of production fragmentation on individual job satisfaction and perceived risk of job loss among German workers, finding that offshoring is negatively associated with job satisfaction.

Studies on the production fragmentation-labour market nexus that offer a broader, cross-country perspective also tend to focus on wages as an indicator of labour conditions (Parteka and Wolszczak-Derlacz 2019, 2020). Nikulin et al. (2021) go a step further and examine how involvement in global production networks affects earnings, working hours and additional payments of workers from 24 European countries. Their results indicate a diversified effect of GVCs on working conditions, depending on the measure used: workers in sectors more deeply involved in GVCs have lower and less stable earnings, but they are also less likely to have to work overtime. The authors call for further research that considers different aspects of workers' well-being.

Another strand of related research deals with worker-level effects of technological progress. It is widely recognised that rapid technological changes are closely linked to labour market outcomes, including wages and employment (for a review, see Goos 2018). An influential stream of literature addressed the displacement effect, typical for highly routine jobs prone to computerisation and robotisation (Frey and Osborne 2017), and the degree of substitution between robots (automation) and workers (Acemoglu and Restrepo 2018, 2020). Following the skill-based technological change and routine-based technological change hypotheses (Acemoglu and Autor 2011; Autor et al. 2003; Goos et al. 2014), low-skilled workers constitute the most vulnerable group, while the highly skilled may benefit from new technologies (for empirical evidence see, among others, Autor et al. 2003; Autor and Handel 2013; Autor and Dorn 2013; Frey and Osborne 2017 for the US and Goos et al. 2014; Marcolin et al. 2016 for the EU).

In the first wave of this literature, workers were typically classified according to the routine content of tasks performed on the job ('task-based approach', see Autor et al. 2003) and occupation-specific indicators of routinisation (Acemoglu et al. 2011; Marcolin et al. 2016; Lewandowski et al. 2019). More recently, similar indicators were constructed for the AI job content, linking the job description with the AI patent text (Webb 2020). These calculated the ‘suitability for machine learning’ (Brynjolfsson et al. 2018) or linked advances in specific applications of AI, such as image recognition, translation, or the ability to play strategic games, to workplace abilities and occupations (Felten et al. 2018, 2019). Studies employing such a methodology show that the implications of the newest ADP technologies are quite complex and differ from a simple case of replacing workers by machines. Considering the employment effect, the linkages depend on the suitability of job-related tasks for the machine learning (Brynjolfsson and Mitchell 2017). In the case of AI exposure, the effects are not entirely related to the displacement effect, and for some workers may even be beneficial: in high-skilled occupations the role of AI solutions may be positive (OECD 2021: 23). Webb (2020) confronts three types of technological exposure (to robots, software and AI) and shows that the effects are diversified. While exposure to robots and software is mainly typical for highly routine jobs, the AI ‘performs tasks that involve detecting patterns, making judgments, and optimization’ (Webb 2020: 3) - tasks typical for many high-level occupations. Felten (2019) shows that ‘despite broad concerns about AI’s potential to substitute for labour, exposure to AI is not significantly related to employment growth, but is positively correlated with wage growth, on average’.

The ADP-focused literature that goes beyond employment or wage analysis and links the newest technologies with working conditions is mainly related to health and safety studies (Badri et al. 2018). Digital technologies have important effects on workers’ well-being, since they may violate the work-life balance or be the source of ‘technostress’ (Tarafdar et al. 2019; Salanova et al. 2014; Berg-Beckhoff et al. 2017). Importantly, it has been shown that AI may additionally impact human-machine interactions, resulting in new and changing work environments (Lane and Saint-Martin 2021).

3. Quantifying working conditions - our empirical approach and evidence on Europe

The quantification of working conditions is not an easy task, given its multidimensional and highly intangible nature. One approach is based on composite indicators of job quality (see an overview in Mira 2021). There are many indicators of job quality in Europe proposed by the ILO, Eurostat, or Eurofound (for a review, see among others Cazes et al. 2015). They rely both on aggregate indices and individual aspects of job quality. For instance, the Job Quality Index developed by the European Trade Union Institute (ETUI) (see Leschke et al. 2008) and calculated for European countries includes such aspects as: (1) wages, (2) non-standard forms of employment, (3) working time and work–life balance, (4) working conditions and job security, (5) skills and career development, and (6) collective interest representation. Periodically published EWCS reports (Eurofound 2017, 2020, 2021) aim to capture the complexity of job quality and rely on indices of: physical environment, work intensity, working time quality, social environment, skills and discretion, prospects, and earnings. EWCS is our primary source of data.

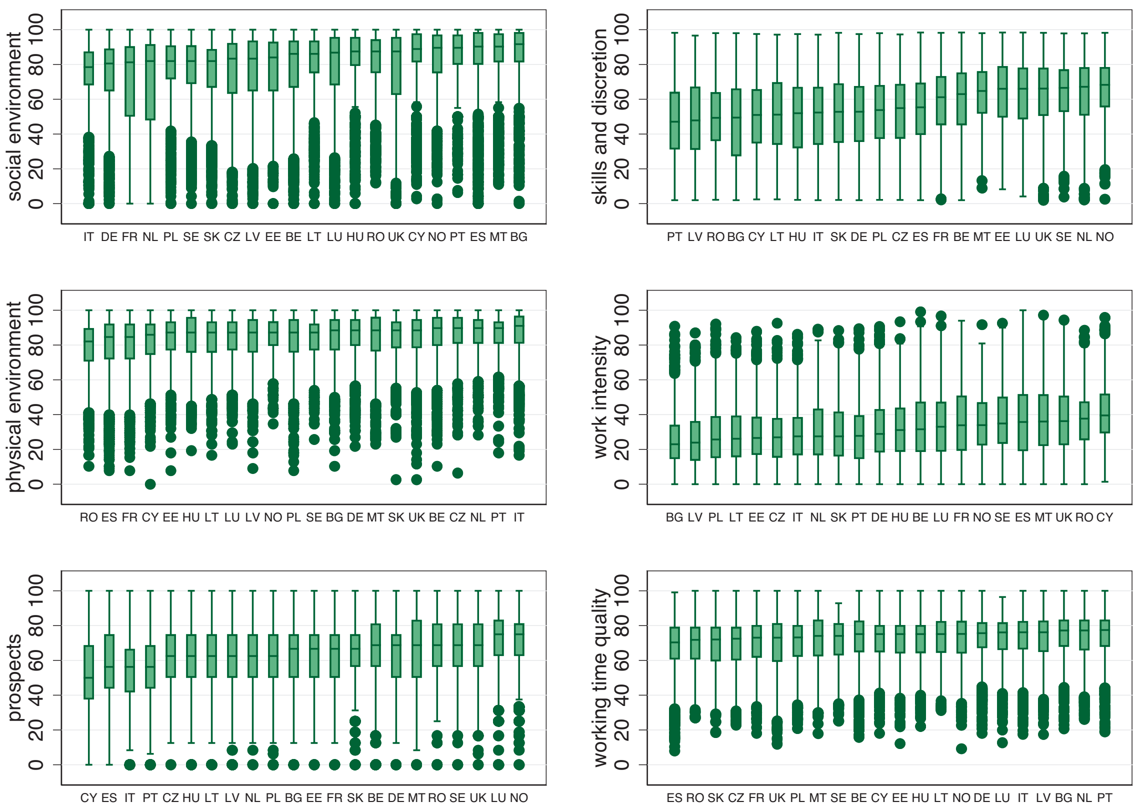
To find the linkages between working conditions, GVC and ADP technology, we use a rich dataset (described in Appendix A) covering workers from 22 European countries[7]. We employ six job quality (JQ) EWCS indices as proxy working conditions (Table 3A in Appendix A presents a detailed overview), combined with information on average hourly wages, derived from the Structure of Earnings Survey (SES). Such an approach enables a complex examination of workers' well-being across Europe, rather than using wages as a sole indicator. Micro-level data is then matched with sector-level indicators of GVC and occupation-level indicators of technological exposure (Appendix A, Table 2A).

Figure 1 presents cross-country variability of six non-monetary dimensions of job quality. In general, we observe heterogeneity, both between European countries and within them (extreme values), but also across different dimensions of well-being at work. For instance, looking at the median values, the best social environment at work is reported in Portugal, Spain, Bulgaria, and Malta, while the worst is in Italy and Germany. Physical environment is appreciated in Portugal, Italy, and the Netherlands, while work intensity

7. The list of countries includes: Belgium, Bulgaria, Cyprus, Czech Republic, Germany, Estonia, Spain, France, Hungary, Italy, Lithuania, Luxembourg, Latvia, Malta, the Netherlands, Norway, Poland, Portugal, Romania, Sweden, Slovakia, and the United Kingdom.

tends to be low in central and eastern European countries. The best places for prospects are the highly developed countries, such as the UK, Luxembourg and Norway.

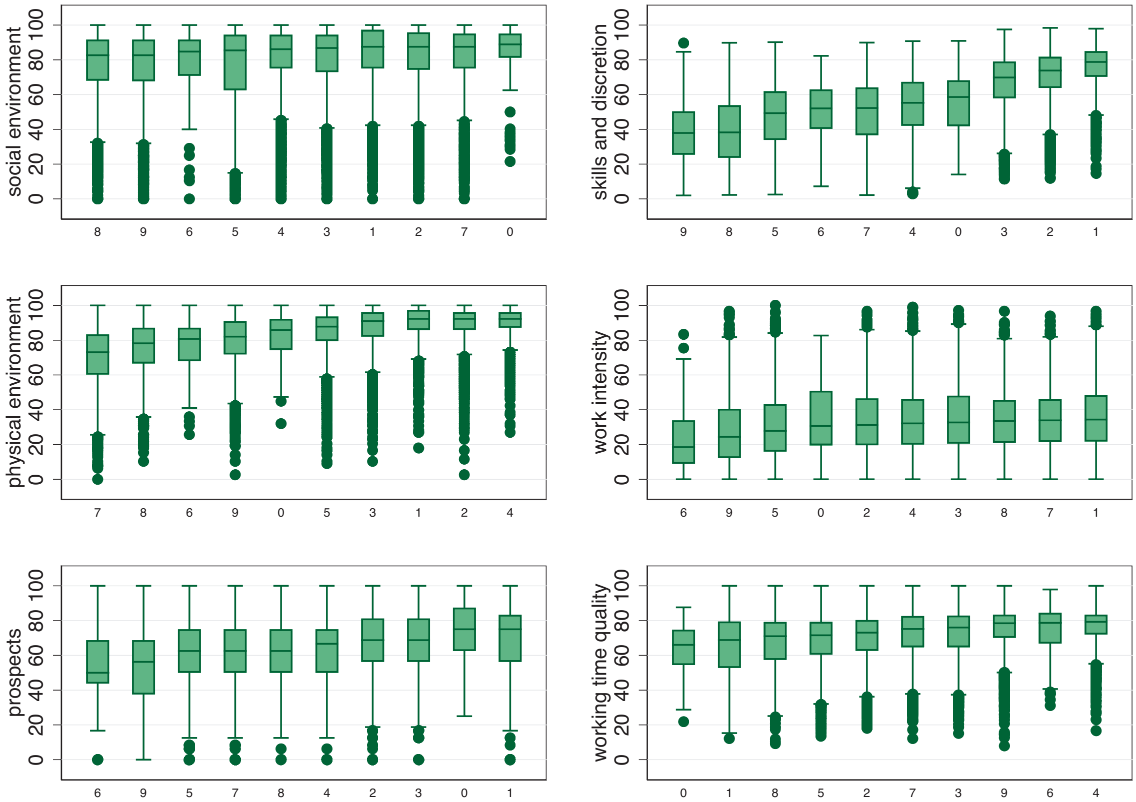
Figure 1 **Job quality in Europe – variation across and within countries**



Notes: High work intensity index should be interpreted as poor job quality.
The list of countries is provided in footnote 7.
The indices of job quality are described in detail in Table 3A in Appendix A.
Source: Own elaboration based on job quality indices from EWCS (2015).

However, boxplots reported in Figure 1 make it clear that country-level mean (or median) values are not informative, and that the analysis should go beyond the aggregate level and explore the occupational specificity of the job quality phenomena. Cross-occupational disparities in job quality indices are shown in Figure 2. In general, low-skilled occupations such as elementary workers, plant and machine operators or assemblers face worse working conditions in such aspects as 'skills and discretion' and prospects. However, once we consider work intensity and work-time quality, then some of the low-skilled occupations (skilled agriculture and fishery workers, elementary workers) benefit the most. Rather, it is the managers who show the worst score in both the work intensity and the working-time quality dimensions. Figure 2 makes it clear that a proper analysis of working conditions must be multidimensional and take different aspects of working environment into account.

Figure 2 **Job quality in Europe – variation across occupations**



Note: Workers grouped into one-digit ISCO-08 occupations: 1. managers, 2. professionals, 3. technicians and associate professionals, 4. clerical support workers, 5. service and sales workers, 6. skilled agricultural and fishery workers, 7. craft and related trades workers, 8. plant and machine workers, 9. elementary workers.
Source: Own elaboration based on job quality indices from EWCS (2015).

4. Determinants of working conditions in Europe in the light of econometric study – the intertwined role of GVCs and technological exposure

Descriptive analyses of working conditions in Europe call for different dimensions to be taken into account: variability across countries, occupations and aspects of work. We use econometric analysis - the detailed technical description of our estimation strategy is provided in Appendix B. To uncover the forces behind observed variability in workers' well-being, we have first considered a wide array of their individual characteristics (see the summary statistics reported in Table 4A). In this section we focus on the conditional (i.e. accounting for individual, sectoral and country-level characteristics) relationship between working conditions faced by European employees, the technological type of their occupations, and GVC intensity. In particular, we want to check whether the impact of GVC on job quality or wages depends on the technological content of jobs. Technically speaking, this is possible by including interaction terms between GVC and technological type of occupation (see model 1 in Appendix B) and interpretation of the interaction graphs. The results separately interpret the findings referring to non-monetary and monetary aspects of work, obtained with job quality indices and wages respectively. Numerous robustness checks and extensions of our analysis are provided in Appendix C.

4.1 Working conditions measured by job quality indices (EWCS)

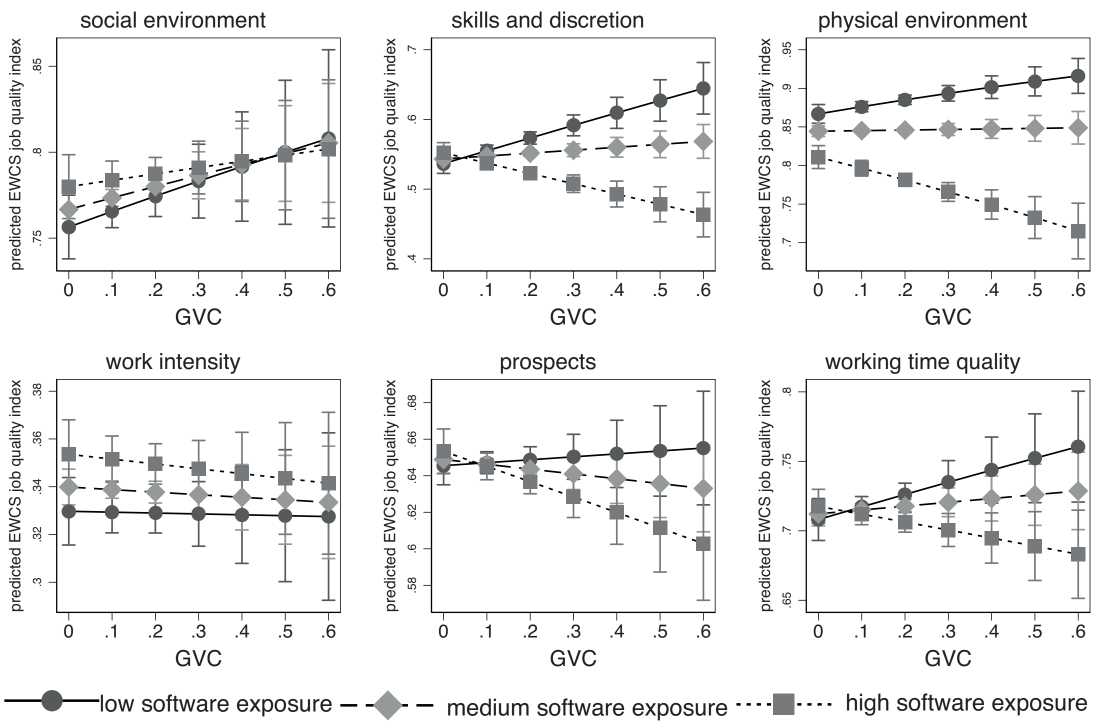
Figure 3 depicts the impact of GVCs on predicted job quality indices at different levels of software, robot and AI exposure: low, medium and high. In each of the graphs, the relative position of the three lines reflects the general differences in job quality across occupations that differ in technological level, while the inclination of the lines shows what happens once GVC intensity increases (the movement to the right along the horizontal axis). Generally, for workers employed in occupations of high software and high robot exposure, job quality tends to be higher than in occupations with medium or low exposure to these technologies. In case of AI exposure, such a relationship is less straightforward. Next, we can confirm that the impact of GVC on job quality depends on the degree of technological exposure – the two phenomena are intertwined. The exact effect varies across types of technological exposures and aspects of job quality.

As far as exposure to software and robots is concerned (Figure 3, panels A and B), predicted job quality tends to increase along with GVC intensification at low levels of technological exposure. The opposite is true once workers are employed in occupations where software exposure is high: job quality tends to decrease as GVC increases. This is particularly visible for such aspects of job quality as: skill and discretion, physical environment, work intensity (bearing in mind that higher work-intensity index implies worse situation), prospects and working-time quality. In the case of social environment, the confidence intervals are too big to draw meaningful conclusions.

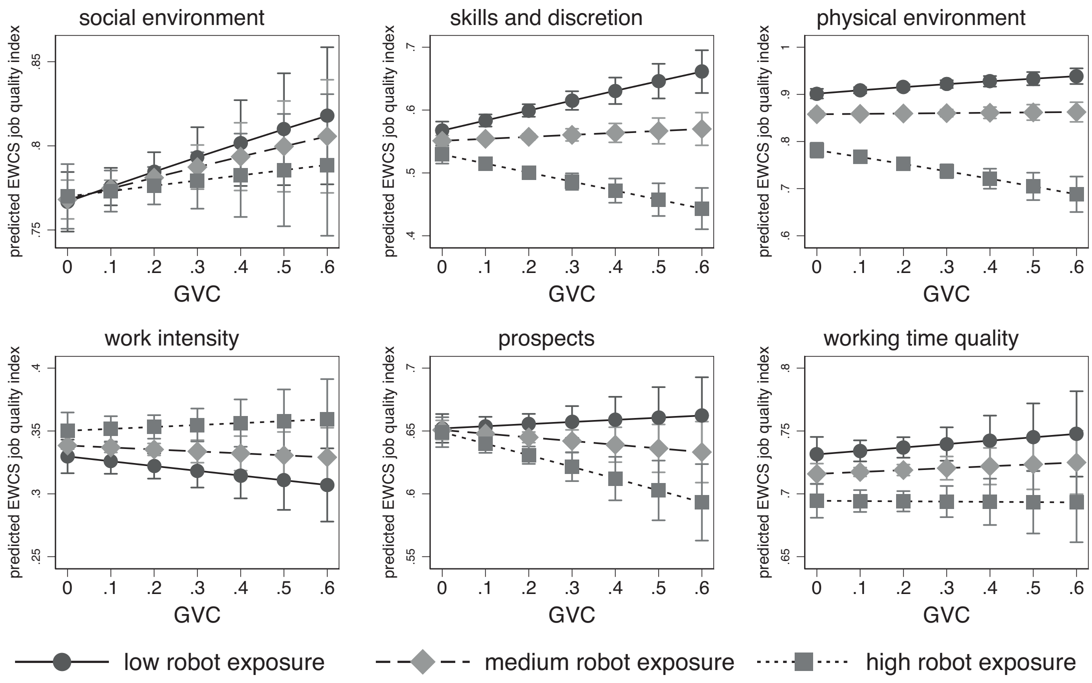
For AI exposure (Figure 3, panel C) the situation is more complex. Once we consider social environment at work and working-time quality, it is better at highly AI exposed jobs but worse in the case of other aspects of job quality. What happens when GVC links intensify? In highly AI-exposed jobs, such aspects as social environment, skills and discretion, and work intensity improve as GVC involvement increases. However, the reverse is true for physical environment and prospects, where the confidence intervals are too high to draw strong-enough conclusions.

Figure 3 **Predicted job quality EWCS indices due to changes in GVC, at different levels of technological exposure of jobs (illustrating the results from Table 1C-3C in Appendix C)**

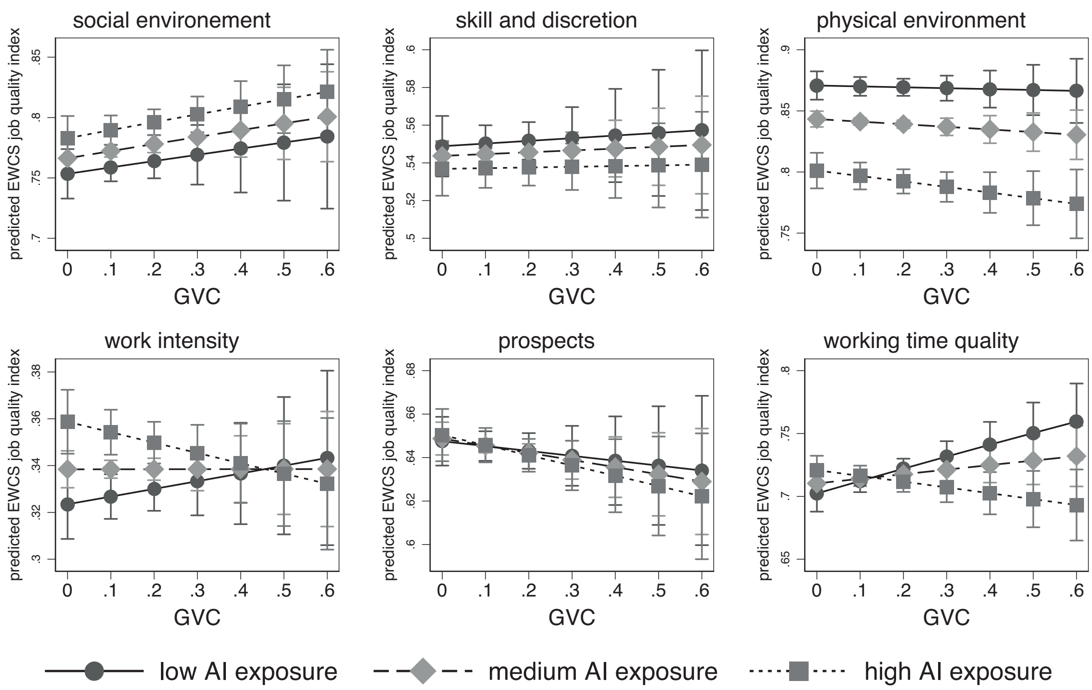
Panel A Software exposure



Panel B Robot exposure



Panel C AI exposure



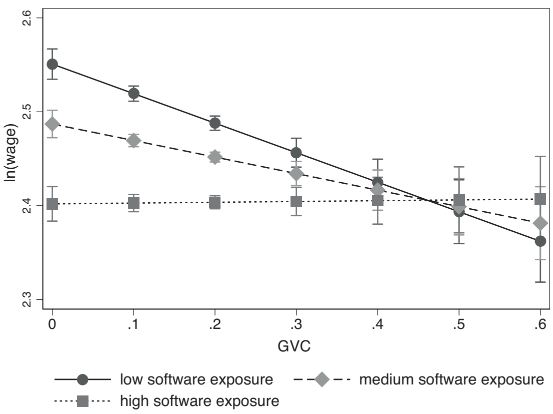
Notes: The lines on the chart correspond to tech exposure level.
Division of occupations into categories of low/medium/high exposure according to the Tech index values (low: tech exposure=10, medium: tech exposure=40, high: tech exposure =80).
Source: Own elaboration based on job quality indices from EWCS (2015) merged with the Word Input-Output Database (WIOD) (2016) and technological exposure indicators from Webb (2020).

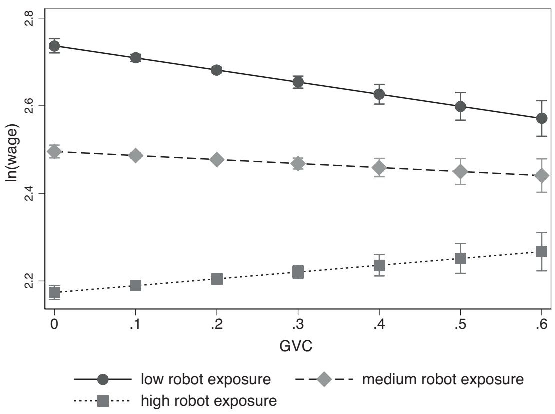
4.2 Working conditions measured by information on wages

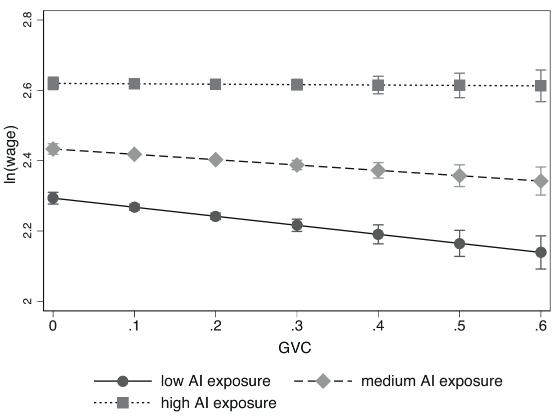
We now turn to a similar analysis but one based on wages as a proxy for working conditions. The estimation results are presented in Table 4C in Appendix C. The corresponding Figure 4 presents the predicted log wages due to changes in GVC at different levels of technological content of jobs (low, medium or high).

On average, in jobs with lower levels of software or robot content, wages are higher, but they decrease as GVC links intensify. At the same time, wages in occupations highly exposed to robots or software increase once sectors become more involved in global structures of production. These trends lead to wage convergence between occupations differing in levels of exposure to computerisation and automation. In highly AI exposed jobs, in turn, the situation is different: wages are higher but rather stable along GVC changes, while salaries in jobs of low and medium AI content further decline as GVC increases. The final effect is thus linked to the divergence in wages typical for occupations with different levels of AI exposure.

Figure 4 **Predicted wages due to the changes in GVC at different levels of digital job content (illustrating the results from Table 4C)**







Notes: The lines on the chart correspond to the tech exposure. Division of occupations into low/medium/high software, robot and AI exposure according to the index values (low: tech exposure =10, medium: tech exposure =40, high: tech exposure =80).
Source: Own elaboration based on job quality indices from EWCS (2015) merged with SES (2014), WIOD (2016) and technological exposure indicators from Webb (2020).

5. Conclusions

A comprehensive view of the joint impact of production internationalisation and digital progress on job quality and social conditions at work is still lacking, including in the European context. The purpose of our analysis was to shed new light on the differences in working conditions across European workers. In particular, we aimed to broaden our understanding of Europeans' well-being at work by: (1) using a multidimensional approach to working conditions' quantification (confronting wages and several aspects of job quality), and (2) assessing jointly the role played by the dependence of European labour markets on GVC and ADP technologies.

Concerning the first point, we hope that our analysis allowed us to put the social dimension into a typical, purely economic view of the impact of GVC/technology on workers. As wages do not capture the full complexity of work-related factors that determine workers' wellbeing, our analysis includes such non-monetary dimensions of job quality as the quality of physical and social environment at work, career development prospects, and work intensity. Indeed, we document that working conditions tend to differ significantly – not only between European countries and across occupations, but also with respect to a particular aspect of working life. The comparison of cross-country averages in job quality indicators is not informative because workers' well-being depends on a specific dimension of job quality, as well as on sector, occupation, and personal characteristics. A detailed cross-country microeconomic perspective is thus necessary.

Concerning the second point, we were particularly interested to see how the two global phenomena of intensification of cross-border production links and rapid progress in digital technologies affect working conditions. To shed more systematic light on the determinants of broadly understood working conditions, we estimated several econometric models linking wages and six job quality indices from EWCS with GVC intensity and technological characteristics of workers' occupation (and several additional controls). We have thus combined three important perspectives present in the related literature: labour economics/sociological research on working conditions and decent work, international economic studies on production fragmentation, and the literature on the effects of technological progress driven by digital solutions.

For instance, we find that on average (i.e., once individual and firms' characteristics are controlled for), job quality in occupations of high software and robot exposure tends to deteriorate as GVC increases, although the effect on monetary wages is negligible. Once we consider the AI exposure of jobs, the links are particularly complex in relation to the job quality indices, while for wages the effect from GVC intensification is also moderate. In this way, we discover that the influence of GVC on wages and different types of job quality measures may be diversified. It creates a need to analyse non-wage aspects in addition to the wages themselves.

We hope that our results, exploring heterogeneity across countries, sectors, occupations and workers, convincingly confirm the multidimensional nature of working conditions. This is particularly important in the light of the efforts of policymakers and institutions to prevent harmful labour market developments and to ensure equal social rights, protection and security. Fair and high-quality job standards are of the highest priority because health problems and worsening job performance caused by bad working conditions require coordinated policy responses.

Our study is based on pre-pandemic data. The next important question that needs to be addressed is how the Covid-19 pandemic has affected working conditions. The impact here is also likely to be unevenly distributed across workers. Some, like medical doctors, are involved in the direct fight against the pandemic, others have had to close their businesses, and many of those working at home have faced increased stress and difficulty in finding work-life balance. All have experienced day-to-day insecurity. Future research describing the impact of the pandemic on workers' well-being is thus needed.

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Appendices

Appendix A Dataset

Our study uses a sample of workers from 22 European countries: Belgium, Bulgaria, Cyprus, Czech Republic, Germany, Estonia, Spain, France, Hungary, Italy, Lithuania, Luxembourg, Latvia, Malta, the Netherlands, Norway, Poland, Portugal, Romania, Sweden, Slovakia, and the UK. The analysis was possible thanks to the merging of several original datasets, as summarised in Table 1A.

Table 1A **Description of data sources**

Database, source	Description	Variable(s) used in our study
European Structure of Earnings Survey (SES). Source: Eurostat	SES contains harmonised data on earnings in EU Member States, Candidate Countries and EFTA countries. The SES is a large enterprise sample survey providing detailed and comparable information on the relationships between the level of remuneration and individual characteristics of employees (sex, age, occupation, length of service, highest educational level attained, etc.) and those of their employer (economic activity, size and location of the enterprise).	*hourly wage, sex, age, education level, full-time/part-time employment, seniority in the company, public/private firm* Wages are derived from SES as mean average gross hourly earnings in the reference month, converted into USD.
European Working Conditions Survey (EWCS), wave 2015 Source: Eurofound	EWCS is a survey focusing on the working conditions of employees across Europe (workers from the European Union, Norway, Switzerland, Albania, Bosnia and Herzegovina, Kosovo, North Macedonia, Montenegro, Serbia, and Turkey) on a harmonised basis. The survey is conducted every five years; the newest available wave is from 2015 (EWCS 2020 fieldwork has been suspended due to Covid-19). The general scope of this survey covers detailed aspects of working conditions, including working time duration, work organisation, learning and training, physical and psychosocial risk factors, health and safety, work-life balance, workers' participation, earnings and financial security.	*six indices measuring job quality* (physical environment, work intensity, working time quality, social environment, skills and discretion, prospects); detailed description provided in Table 3A (Appendix A) and individual characteristics such as *sex, age, education, skill level, type of contract, part-time/full-time employment.*
Word Input-Output Database (WIOD), release 2016 Source: wiod.org	WIOD covers input-output data for 43 countries and 56 sectors according to the ISIC Rev. 4 classification. WIOD data enabled us to compute several measures of global value chain (GVC) intensity.	*FVA/Export:* Foreign value added in exports GII: global import intensity of production—intermediate imports along the value chain divided by the value of the final product *Industry-level productivity*
Institutional Characteristics of Trade Unions, Wage Setting, State Intervention and Social Pacts (ICTWSS) Source: Visser (2019)	ICTWSS contains country-level data describing the institutional environment in the labour market (e.g. the collective bargaining scheme).	*Coord:* coordination of wage-setting OCG: general opening clauses in collective agreement *BARG:* the predominant level at which wage bargaining takes place

Database, source	Description	Variable(s) used in our study
Penn World Table (PWT version 9.1) Source: www.ggdc.net/pwt	PWT is a source of additional country-level data on the magnitude of GDP, import, export, etc.	*Export*–share of merchandise exports in real GDP at current PPPs *Import*–share of merchandise imports in real GDP at current PPPs

Table 2A **List of occupations and their technological classification**

ISCO 08 two-digit code	Software exposure	Robot exposure	AI exposure
11	45	21	56
12	46	23	70
13	51	26	71
14	50	26	68
21	62	38	84
22	39	24	56
23	11	11	19
24	25	13	57
25	71	34	83
26	29	19	51
31	76	59	77
32	53	55	52
33	35	24	55
34	39	37	46
35	85	57	81
41	33	42	29
42	41	34	36
43	38	22	35
44	33	38	25
51	22	48	24
52	24	38	19
53	29	49	23
54	48	51	56
61	84	75	90
62	81	70	69
63	85	83	71
71	59	75	49
72	63	75	57
73	55	62	57
74	62	64	67
75	56	65	59
81	76	75	63
82	72	74	52
83	77	84	61
91	48	83	23
92	87	86	77
93	56	78	35
94	6	70	11
95	39	10	13
96	75	83	44

Note: Measures of software, robot and AI exposure are based on percentiles as proposed by Webb (2020).

Table 3A **Job quality indices according to EWCS (2015)**

Job quality index	Main indicators	Detailed indicators
physical environment	■ posture-related (ergonomic) ■ ambient (vibration, noise, temperature) ■ biological and chemical	– vibrations from hand tools, machinery – noise so loud that you would have to raise your voice to talk to people – high temperatures that make you perspire even when not working – low temperatures whether indoors or outdoors – breathing in smoke, fumes (such as welding or exhaust fumes), powder or dust (such as wood dust or mineral dust) – handling, or being in skin contact with, chemical products or substances – tobacco smoke from other people – handling, or being in direct contact with, materials that could be infectious, such as waste, bodily fluids, laboratory materials, etc. – tiring or painful positions – lifting or moving people – carrying or moving heavy loads – repetitive hand or arm movements
work intensity	■ quantitative demands ■ pace determinants and interdependency ■ emotional demands	– working at very high speed (three-quarters of the time or more) – working to tight deadlines (three-quarters of the time or more) – enough time to get the job done (never or rarely) – frequent disruptive interruptions – interdependency: three or more pace determinants – work pace dependent on the work done by colleagues – work pace dependent on direct demands from people such as customers, passengers, pupils, patients, etc. – work pace dependent on numerical production targets or performance targets – work pace dependent on the direct control of your boss – hiding your feelings at work (most of the time or always) – handling angry clients, customers, patients, pupils, etc. (three-quarters of the time or more) – being in situations that are emotionally disturbing (a quarter of the time or more)
working time quality	■ duration ■ atypical working time ■ working time arrangements ■ flexibility	– long working hours (48 hours or more a week) – no recovery period (less than 11 hours between 2 working days in the past month) – long working days (10 hours or more a day) – night work; Saturday work; Sunday work; shift work – control over working time arrangements – change in working time arrangements – very easy to arrange to take an hour off during working hours to take care of personal or family matters – work in free time to meet work demands (several times a month)
social environment	■ adverse social behaviour ■ social support ■ management quality	– exposure to verbal abuse – exposure to unwanted sexual attention – exposure to threats – exposure to humiliating behaviours – exposure to physical violence – exposure to sexual harassment – exposure to bullying/harassment – your immediate boss respects you as a person: strongly agree and tend to agree – your immediate boss gives you praise and recognition when you do a good job: strongly agree and tend to agree – your immediate boss is successful in getting people to work together: strongly agree and tend to agree – your immediate boss is helpful in getting the job done: strongly agree and tend to agree – your immediate boss provides useful feedback in your work: strongly agree and tend to agree – your immediate boss encourages and supports your development: strongly agree and tend to agree – help and support from colleagues (most of the time/always) – help and support from your manager (most of the time/always)

Job quality index	Main indicators	Detailed indicators
skills and discretion	■ cognitive dimension ■ decision latitude ■ organisational participation ■ training	– solving unforeseen problems – carrying out complex tasks – learning new things – working with computers, smartphones and laptops, etc. (at least a quarter of the time) – ability to apply your own ideas in work ('sometimes', 'most of the time' and 'always') – ability to choose or change the order of tasks – ability to choose or change speed or rate of work – ability to choose or change methods of work – having a say in the choice of work colleagues ('always' or 'most of the time') – consulted before objectives are set for own work ('always' or 'most of the time') – involved in improving the work organisation or work processes of own department or organisation ('always' or 'most of the time') – ability to influence decisions that are important for your work ('always' or 'most of the time') – training paid for or provided by employer over the past 12 months (or paid by oneself if self-employed) – on-the-job training over the past 12 months
prospects	■ employment status ■ career prospects ■ job security ■ downsizing	– what kind of employment contract do you have in your main job? – my job offers good prospects for career advancement (strongly agree and tend to agree) – I might lose my job in the next six months (strongly agree and tend to agree) – during the past three years (or past year according to seniority in the company), has the number of employees at your workplace increased, stayed the same or decreased?

Source: Own elaboration based on EWCS 2015 report (Eurofound 2017).

Table 4A **Summary statistics of the variables used in estimations**

	N	Mean	Std. Dev.	Min	Max
Hourly wage [in USD] – SES dataset	9526268	16.75	14.40	1.25	111.34
Job quality indices – EWCS dataset					
social environment	25681	77.49	23.62	0.00	100.00
skills and discretion	27694	55.51	21.36	1.98	98.37
physical environment	27679	83.73	14.54	0.00	100.00
work intensity	27612	32.92	18.72	0.00	100.00
prospects	27598	63.02	19.74	0.00	100.00
working time	27694	70.92	13.95	7.97	100.00
Technological exposure					
Software exposure	27585	43.28	19.62	6.00	87.00
Robot exposure	27585	46.71	23.33	10.00	86.00
AI exposure	27585	44.01	20.11	11.00	90.00
AIOE	27585	-0.02	0.87	-1.53	1.28
Individual, job and firm characteristics (EWCS dataset)					
sex	27689	0.48	0.50	0.00	1.00
ageyoung	27694	0.16	0.37	0.00	1.00
ageaverage	27694	0.47	0.50	0.00	1.00
ageold	27694	0.34	0.47	0.00	1.00
loweduc	27576	0.18	0.38	0.00	1.00
mededuc	27576	0.49	0.50	0.00	1.00
higheduc	27576	0.33	0.47	0.00	1.00
Skill1	27585	0.11	0.31	0.00	1.00
Skill2	27585	0.52	0.50	0.00	1.00
Skill3	27585	0.12	0.32	0.00	1.00
Skill4	27585	0.26	0.44	0.00	1.00
Unlimited	23979	0.78	0.41	0.00	1.00
Part time	26201	0.21	0.40	0.00	1.00
Individual, job and firm characteristics (SES dataset)					
sex	9526356	0.50	0.50	0.00	1.00
ageyoung	9526356	0.17	0.38	0.00	1.00
ageaverage	9526356	0.52	0.50	0.00	1.00
ageold	9526356	0.31	0.46	0.00	1.00
loweduc	9526356	0.16	0.37	0.00	1.00
mededuc	9526356	0.45	0.50	0.00	1.00
higheduc	9526356	0.39	0.49	0.00	1.00
Full time	9526356	0.82	0.39	0.00	1.00
shortdur	9526356	0.13	0.34	0.00	1.00
meddur	9526356	0.30	0.46	0.00	1.00
logdur	9526356	0.37	0.48	0.00	1.00
vlongdur	9526356	0.20	0.40	0.00	1.00
public	9242482	0.37	0.48	0.00	1.00

	N	Mean	Std. Dev.	Min	Max
GVC measures					
FVA/Export	27653	0.14	0.10	0.01	0.70
GII	27694	0.25	0.18	0.00	0.99

Notes: For SES data we use weighted statistics with weights based on the rescaled grossing-up factor for employees (from SES), normalised by the number of observations per country.
Job quality indices may range from 0-100 and cover six dimensions as described in Table 3A.
Individual characteristics (both from EWCS and SES): *sex* (0 for female, 1 for male); age variable recoded into *ageyoung* (below 30 years), *ageaverage* (30-49) and *ageold* (50 and more); educational level means the highest completed level of education according to the ISCED-2011 classification: *loweduc* for low educational attainment level; *mededuc* for medium educational attainment level; *higheduc* for high educational attainment level.
Additional individual characteristics from EWCS: skill level according to ISCO skill level: *Skill1, Skill2, Skill3, Skill4; Unlimited* (1 for contract of unlimited duration, 0 for otherwise); *Part time* (1 for full-time employment, 0 otherwise).
Additional individual characteristics from SES: FT (1 if full-time employment, 0 for part-time employment); length of employment in the company: *shortdur* (less than 1 year), *meddur* (1 to 4 years), longdur (5 to 14 years), *vlongdur* (15 years and more); *public* (1 for public, 0 for private companies).
Source: Own elaboration based on job quality indices from EWCS (2015), wages from SES (2014) and technological exposure indicators from Webb (2020), AIOE from Felten et al. (2019) and sectoral data from WIOD (2016).

Appendix B Details on the econometric estimation (methodology)

Our key task is to estimate the relationship between different aspects of working conditions (quantified mainly through job quality (*JQ*) indices), GVC intensity, and digital content of jobs (ADP specialisation). We run the following augmented Mincerian regression:

$$JQ^{k}_{iojsc} = \alpha + \beta_1 Worker_i + \beta_2 Firm_j + \beta_3 Prod_s + \beta_4 GVC_{sc} + \beta_5 Tech_o + \beta_6 GVC_{sc} \times Tech_o + D_c + D_s + \varepsilon_{iojsc} \quad (1)$$

where i - worker; o – occupation, j – company, s - sector of employment, c – country and k – the type of job quality EWCS index. As an alternative to *JQ*, we employ the log of wage. In *JQ* estimates (relying on EWCS data) the set of individual characteristics ($Worker_i$) include sex, age, education, skills (four types, based on occupation). In case of wage regression, based on more detailed SES data, for $Worker_i$ we use: sex, age, education, type of employment (full-time/part-time job binary variable). $Firm_j$ stands for job characteristics related to firm: in models using EWCS indices we employ the type of contract (unlimited/temporary), part time or full time; in wage regression we use: length of service in the enterprise, full time/part time and form of economic and financial control (public/private). Sector productivity ($Prod_s$, expressed in logs) equal to the ratio of value added to the total number of hours worked by employees. GVC_{sc} is a proxy of country sector-specific involvement in GVCs, expressed as the share of foreign value added (FVA) in exports (Wang et al. 2013). $Tech_o$ reflects technology-related features of the occupation, captured via software, robot or AI exposure measures (Webb, 2020). We also add the interaction between *GVC* and *Tech*, which takes into account the possibility that the effect of GVC on working conditions depends on the type of technological exposure ($GVC_{sc}xTech_o$). The marginal effect of GVC on job quality is equal to $\frac{\delta JQ}{\delta GVC} = \beta_4 + \beta_6 Tech$ (similarly for wages). Additionally, we include country and sector-fixed effects: D_c should clear all country-specific characteristics such as labour market regulations, and D_s the remaining characteristics of sectors. The summary statistics of all variables are presented in Table 4A in Appendix A.

In case of model relying on EWCS *JQ* indices (in the range 0-1), equation (1) is estimated by fractional probit[8], in case of wage-based model we use weighted OLS. Weights are calculated on the bases of SES grossing-up factor adjusted to the number of observations per country (assuring that each country is equally represented in the sample). Regression for both types of the dependent variable are estimated with robust standard errors clustered at the country-industry level.

8. We use the command: fracreg in STATA.

Appendix C Results

Appendix C1 Estimates based on job quality EWCS indices

The estimation result for equation (1) obtained with six different *JQ* indices from EWCS and three types of technological exposure of jobs are presented in Tables 1C-3C.

We start the interpretation from the results concerning individual characteristics of workers and obtained with software exposure employed as *Tech* – Table 1C. Once *Tech* is measured via robot and AI exposure (Table 2C and Table 3C), the relationships between *JQ* indices and individual and job characteristics are similar.

In case of social environment, male workers are characterised by higher probability of increase in this aspect (the same for prospects and work intensity – lower work intensity implies better working conditions). Female workers are better off in the case of physical environment and working time. Younger workers are more likely to face worse physical environment, work intensity and working time, but higher prospects. Workers of medium age are better off than older workers with respect to social environment and prospects, while the opposite is true for other job quality indices. Concerning education variables, we compare employees with low and medium education with highly educated employees. Except for working intensity and working time, workers with low and medium education are more likely to have better job quality. As far as skills are concerned, workers with higher education may benefit from such aspects of job quality as social environment, skills and discretion, physical environment, and prospects. The opposite is the case for work intensity and working time. Workers with unlimited contracts are more likely to experience higher job quality in all aspects. Those working part time are better off as far as physical environment, work intensity and working time are concerned.

These variables serve as individual-level controls. The variables we are mainly interested in are *GVC*, *Tech* and the interaction term between them. If the interaction is statistically significant, then the relationship between *GVC* and *JQ* depends on the degree of technological exposure. The results are illustrated in Figure 3 and interpreted in the main text.

Table 1C **Estimation results, determinants of job quality EWCS indices, *Tech* measured as software exposure**

	Dep.var: job quality EWCS indices					
	Social environment	Skills and discretion	Physical environment	Work intensity	Prospects	Working time
ln_prod	0.000	0.000	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
sex	0.029***	0.008	-0.074***	-0.045***	0.018**	-0.083***
	[0.007]	[0.013]	[0.012]	[0.009]	[0.007]	[0.007]
ageyoung	0.003	0.003	-0.078***	0.077***	0.188***	-0.035***
	[0.010]	[0.018]	[0.012]	[0.011]	[0.011]	[0.008]
ageaverage	0.015**	-0.047***	-0.058***	0.075***	0.070***	-0.036***
	[0.007]	[0.012]	[0.008]	[0.008]	[0.007]	[0.006]
loweduc	-0.228***	0.017	-0.171***	-0.092***	-0.055***	0.026**
	[0.013]	[0.020]	[0.019]	[0.015]	[0.011]	[0.011]
mededuc	-0.120***	0.033**	-0.137***	-0.050***	-0.031***	0.013*
	[0.009]	[0.015]	[0.011]	[0.009]	[0.009]	[0.007]
Skill1	-0.691***	-0.095***	-0.249***	-0.131***	-0.187***	0.152***
	[0.017]	[0.027]	[0.024]	[0.020]	[0.015]	[0.015]
Skill2	-0.502***	-0.070***	-0.174***	-0.053***	-0.124***	0.053***
	[0.013]	[0.019]	[0.020]	[0.013]	[0.011]	[0.012]
Skill3	-0.097***	-0.015	-0.001	-0.021	-0.056***	0.078***
	[0.012]	[0.021]	[0.018]	[0.014]	[0.013]	[0.012]
Unlimited	0.121***	0.057***	-0.008	0.037***	0.583***	0.033***
	[0.009]	[0.016]	[0.012]	[0.010]	[0.010]	[0.009]
Part time	-0.058***	0.004	0.051***	-0.072***	-0.066***	0.110***
	[0.009]	[0.016]	[0.012]	[0.012]	[0.009]	[0.009]
GVC	0.625***	0.322	0.602***	-0.004	0.085	0.332**
	[0.136]	[0.237]	[0.198]	[0.128]	[0.107]	[0.164]
Tech	0.001	0.001	-0.003***	0.001*	0	0
	[0.000]	[0.001]	[0.001]	[0.000]	[0.000]	[0.000]
GVC xTech	-0.013***	-0.002	-0.014***	-0.001	-0.004**	-0.006**
	[0.002]	[0.004]	[0.003]	[0.002]	[0.002]	[0.003]
N	22524	22350	22523	22478	22521	22524

Notes: Sex (male=1, female=0). The reference categories: *ageold* (50 and more), *higheduc* (tertiary education up to 4 years and more than 4 years), Skill category (*Skill4*), Unlimited contract (*Unlimited*), *Part time* (=1 if part-time employment).
Country and sector-fixed effects included.
Robust standard errors, cluster at country-industry level. *p ≤ .10, **p≤ .05, ***p ≤.0.01
Source: Own calculation based on data from EWCS, WIOD and Webb (2020).

Table 2C **Estimation results, determinants of job quality EWCS indices, *Tech* measured as robot exposure**

	Dep.var: job quality EWCS indices					
	Social environment	Skills and discretion	Physical environment	Work intensity	Prospects	Working time
ln_prod	0.000	0.000	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
sex	0.040***	0.016	-0.062***	-0.045***	0.021***	-0.076***
	[0.008]	[0.013]	[0.012]	[0.010]	[0.007]	[0.007]
ageyoung	0.003	0.002	-0.080***	0.077***	0.188***	-0.036***
	[0.010]	[0.018]	[0.012]	[0.011]	[0.011]	[0.008]
ageaverage	0.015**	-0.047***	-0.057***	0.075***	0.070***	-0.036***
	[0.007]	[0.012]	[0.007]	[0.008]	[0.007]	[0.006]
loweduc	-0.216***	0.021	-0.145***	-0.095***	-0.051***	0.033***
	[0.013]	[0.021]	[0.018]	[0.015]	[0.011]	[0.011]
mededuc	-0.115***	0.035**	-0.125***	-0.051***	-0.030***	0.017**
	[0.009]	[0.015]	[0.011]	[0.009]	[0.009]	[0.007]
Skill1	-0.537***	-0.071*	0.198***	-0.180***	-0.150***	0.245***
	[0.023]	[0.039]	[0.040]	[0.028]	[0.020]	[0.022]
Skill2	-0.419***	-0.061***	0.086***	-0.083***	-0.103***	0.101***
	[0.016]	[0.023]	[0.026]	[0.016]	[0.013]	[0.013]
Skill3	-0.058***	-0.004	0.110***	-0.032**	-0.047***	0.103***
	[0.013]	[0.022]	[0.021]	[0.014]	[0.013]	[0.013]
Unlimited	0.121***	0.057***	-0.008	0.037***	0.583***	0.032***
	[0.009]	[0.016]	[0.012]	[0.010]	[0.010]	[0.009]
Part time	-0.059***	0.003	0.054***	-0.073***	-0.067***	0.110***
	[0.009]	[0.016]	[0.012]	[0.012]	[0.009]	[0.009]
GVC	0.548***	0.332*	0.559***	-0.129	0.092	0.097
	[0.121]	[0.189]	[0.175]	[0.101]	[0.104]	[0.136]
Tech	-0.001***	0	-0.007***	0.001*	0	-0.002***
	[0.000]	[0.001]	[0.001]	[0.000]	[0.000]	[0.000]
GVCxTech	-0.012***	-0.003	-0.013***	0.002	-0.004***	-0.001
	[0.002]	[0.003]	[0.003]	[0.002]	[0.002]	[0.002]
N	22524	22350	22523	22478	22521	22524

Note: As under Table 1C.
Source: Own calculation based on data from EWCS, WIOD and Webb (2020).

Table 3C **Estimation results, determinants of job quality EWCS indices, *Tech* measured as AI exposure**

	Dep.var: job quality EWCS indices					
	Social environment	Skills and discretion	Physical environment	Work intensity	Prospects	Working time
ln_prod	0.000	0.000	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
sex	0.022***	0.002	-0.085***	-0.045***	0.015**	-0.087***
	[0.007]	[0.013]	[0.012]	[0.009]	[0.008]	[0.007]
ageyoung	0.003	0.003	-0.077***	0.077***	0.188***	-0.035***
	[0.010]	[0.018]	[0.012]	[0.011]	[0.011]	[0.008]
ageaverage	0.014**	-0.047***	-0.059***	0.075***	0.070***	-0.036***
	[0.007]	[0.012]	[0.008]	[0.008]	[0.007]	[0.006]
loweduc	-0.232***	0.015	-0.179***	-0.092***	-0.056***	0.023**
	[0.013]	[0.020]	[0.019]	[0.015]	[0.011]	[0.011]
mededuc	-0.121***	0.031**	-0.138***	-0.050***	-0.031***	0.012*
	[0.009]	[0.015]	[0.011]	[0.009]	[0.009]	[0.007]
skill1	-0.717***	-0.039	-0.444***	-0.092***	-0.189***	0.144***
	[0.020]	[0.029]	[0.029]	[0.021]	[0.017]	[0.019]
skill2	-0.517***	-0.035	-0.284***	-0.031**	-0.125***	0.049***
	[0.016]	[0.022]	[0.024]	[0.014]	[0.013]	[0.016]
skill3	-0.109***	-0.007	-0.061***	-0.013	-0.058***	0.072***
	[0.012]	[0.021]	[0.018]	[0.013]	[0.013]	[0.013]
unlimited	0.121***	0.056***	-0.007	0.036***	0.583***	0.033***
	[0.009]	[0.016]	[0.012]	[0.010]	[0.010]	[0.009]
part time	-0.058***	0.005	0.051***	-0.071***	-0.066***	0.111***
	[0.009]	[0.016]	[0.012]	[0.012]	[0.009]	[0.009]
GVC	0.042	0.164	-0.018	0.122	-0.053	0.353***
	[0.147]	[0.253]	[0.166]	[0.131]	[0.115]	[0.125]
Tech	0	0.001*	-0.004***	0.001***	0	0.001*
	[0.001]	[0.001]	[0.001]	[0.000]	[0.000]	[0.000]
GVCxTech	0	0.001	-0.002	-0.003	-0.001	-0.006***
	[0.002]	[0.004]	[0.003]	[0.002]	[0.002]	[0.002]
N	22524	22350	22523	22478	22521	22524

Note: As under Table 1C.
Source: Own calculation based on data from EWCS, WIOD and Webb (2020).

Appendix C2 Estimates based on wages

We repeat the analysis, but this time the dependent variable is the log of wage and the estimation method is weighted OLS with robust errors clustered on the country-industry level. The detailed results are reported in Table 4C. Generally, males, younger workers, those with lower education and less experience obtain lower wages, which is in line with the literature on wage determination (for example, Nikulin 2021). Also, full-time workers and those employed in public companies get higher remuneration. The results taking into account the change in wages due to rise in GVC intensity (the interaction: *GVCxTech*) are described in the main text.

Table 4C **Estimation results: determinants of wages**

	Software exposure	Robot exposure	AI exposure
	(1)	(2)	(3)
ln_prod	0.098***	0.093***	0.099***
	[0.020]	[0.020]	[0.020]
sex	0.145***	0.167***	0.097***
	[0.005]	[0.005]	[0.005]
ageyoung	-0.142***	-0.148***	-0.132***
	[0.012]	[0.010]	[0.012]
ageaverage	-0.008	-0.014***	-0.008
	[0.006]	[0.005]	[0.006]
loweduc	-0.492***	-0.323***	-0.453***
	[0.017]	[0.013]	[0.021]
mededuc	-0.357***	-0.243***	-0.328***
	[0.013]	[0.011]	[0.016]
full time	0.060***	0.041***	0.035***
	[0.011]	[0.010]	[0.010]
shortdur	-0.303***	-0.270***	-0.290***
	[0.018]	[0.014]	[0.019]
meddur	-0.213***	-0.190***	-0.206***
	[0.011]	[0.010]	[0.011]
longdur	-0.122***	-0.107***	-0.118***
	[0.009]	[0.008]	[0.008]
public	0.038**	0.037**	0.038***
	[0.015]	[0.015]	[0.014]
GVC	-0.361**	-0.456***	-0.401***
	[0.150]	[0.127]	[0.154]
Tech	-0.002***	-0.007***	0.004***
	[0.001]	[0.000]	[0.001]
GVCxTech	0.005*	0.007***	0.004*
	[0.003]	[0.002]	[0.002]
R^2	0.8	0.82	0.81
N	9218140	9218140	9218140

Notes: Sex (male=1, female=0).
Reference categories: *ageold* (50 and more), *higheduc* (tertiary education up to 4 years and more than 4 years), *Full time* (=1 if full-time employed), very long duration experience in the unit (*vlongdur*), country and sector fixed effects included.
Robust standard errors clustered at country-sector level. *p ≤ .10, **p≤ .05, ***p ≤.0.01.
Source: Own calculation based on data from SES, WIOD and Webb (2020).

Appendix C3 Robustness checks and extensions

In order to check the sensitivity of the results, we run numerous robustness checks (provided as supplementary materials). We start with the sensitivity analysis for wages. First, we consider cross-country differences in labour market institutional coordination, specifically wage-bargaining schemes. The data comes from the Database on Institutional Characteristics of Trade Unions, Wage Setting, State Intervention and Social Pacts (Visser 2019). We take into account the recoded variable of the coordination of wage-setting (*Coord*) where 1 denotes centralised or industry-level bargaining, and 0 is for countries with mixed industry and firm-level bargaining (Table 1S). Then we employ the variables *OCG*[9] (general opening clauses in collective agreement) and wage bargaining (*barg3*[10]) (Tables 2S and 3S). Additionally, we add country-level variables, such as import and export share of GDP as measures of trade openness (Tables 4S and 5S). Neither augmenting the regression by variables describing wage-setting mechanism nor by country-specific openness measures alter the baseline results.

Next, we change the measure of GVC intensity, substituting FVA share in exports by global import intensity of production (GII) as defined by Timmer et al. (2016). GII is based on the ratio of all intermediate imports summed along the entire chain (not only the previous stage) divided by the value of the final product. Our main results hold (Table 6S).

Then we substitute the Webb's index of AI exposure by *AI Occupational Impact* (AIOE) *index* from Felten et al. (2018, 2019). Wages are higher for workers more exposed to AI, and they do change significantly with the rise of GVC participation (Table 7S). The same is true for job quality indices (Table 26S). Generally, this finds, along with previous studies, for example, Felten et al. (2019), that AI-exposed occupations are characterised by positive (minor) change in wages.

We repeat the same robustness checks for all EWCS job quality indices (Tables 8S-26S) and our main conclusion is confirmed.

9. The value 1 means that agreements contain general opening clauses (renegotiation of contractual provisions at lower levels, under specified conditions) and the value 0 is for agreements containing no opening clauses.

10. The predominant level at which wage bargaining takes place, in general: 1: local or company level; 2: industry level; 3: central level.

Appendix D Supplementary materials to the text

Table 1S **Estimation results: determinants of wages, additional variable *Coord* (wage-setting coordination)**

	Software exposure	Robot exposure	AI exposure
	(1)	(2)	(3)
ln_prod	0.098***	0.093***	0.099***
	[0.020]	[0.020]	[0.020]
sex	0.145***	0.167***	0.097***
	[0.005]	[0.005]	[0.005]
ageyoung	-0.142***	-0.148***	-0.132***
	[0.012]	[0.010]	[0.012]
ageaverage	-0.008	-0.014***	-0.008
	[0.006]	[0.005]	[0.006]
loweduc	-0.492***	-0.323***	-0.453***
	[0.017]	[0.013]	[0.021]
mededuc	-0.357***	-0.243***	-0.328***
	[0.013]	[0.011]	[0.016]
full time	0.060***	0.041***	0.035***
	[0.011]	[0.010]	[0.010]
shortdur	-0.303***	-0.270***	-0.290***
	[0.018]	[0.014]	[0.019]
meddur	-0.213***	-0.190***	-0.206***
	[0.011]	[0.010]	[0.011]
longdur	-0.122***	-0.107***	-0.118***
	[0.009]	[0.008]	[0.008]
public	0.038**	0.037**	0.038***
	[0.015]	[0.015]	[0.014]
coord	0.171***	0.174***	0.200***
	[0.033]	[0.034]	[0.037]
GVC	-0.361**	-0.456***	-0.401***
	[0.150]	[0.127]	[0.154]
Tech	-0.002***	-0.007***	0.004***
	[0.001]	[0.000]	[0.001]
GVCxTech	0.005*	0.007***	0.004*
	[0.003]	[0.002]	[0.002]
R^2	0.8	0.82	0.81
N	9218140	9218140	9218140

Note: Personal and firms' characteristics included as in Table 4C; country and sector fixed effects included; variable coordination of wage setting (*Coord*) takes value 1 for centralised or industry-level bargaining; 0 is for countries with mixed industry and firm-level bargaining.
Source: Own calculation based on data from SES, WIOD, Visser (2016) and Webb (2020).

Table 2S **Estimation results: determinants of wages, additional variable: *OCG* (general opening clauses)**

	Software exposure (1)	Robot exposure (2)	AI exposure (3)
ln_prod	0.128***	0.121***	0.133***
	[0.028]	[0.028]	[0.029]
sex	0.136***	0.154***	0.094***
	[0.007]	[0.007]	[0.006]
ageyoung	-0.232***	-0.228***	-0.221***
	[0.015]	[0.014]	[0.015]
ageaverage	-0.052***	-0.053***	-0.051***
	[0.006]	[0.006]	[0.006]
loweduc	-0.462***	-0.326***	-0.418***
	[0.018]	[0.015]	[0.019]
mededuc	-0.316***	-0.229***	-0.279***
	[0.013]	[0.012]	[0.015]
full time	0.073***	0.052***	0.050***
	[0.011]	[0.011]	[0.011]
shortdur	-0.271***	-0.250***	-0.260***
	[0.014]	[0.013]	[0.014]
meddur	-0.208***	-0.191***	-0.202***
	[0.013]	[0.013]	[0.013]
longdur	-0.116***	-0.104***	-0.112***
	[0.010]	[0.010]	[0.010]
public	0.057***	0.053***	0.061***
	[0.016]	[0.016]	[0.015]
OCG	-0.937***	-0.951***	-0.947***
	[0.045]	[0.046]	[0.047]
GVC	-0.22	-0.341**	-0.382**
	[0.157]	[0.148]	[0.171]
Tech	-0.001	-0.006***	0.004***
	[0.001]	[0.000]	[0.001]
GVCxTech	-0.002	0.001	0.001
	[0.002]	[0.002]	[0.002]
R^2	0.82	0.83	0.83
N	4598689	4598689	4598689

Note: Personal and firms' characteristics included as in Table 4C; country and sector fixed effects included; variable OCG (general opening clauses in collective agreement) takes value 1 if agreements contain OCGs (renegotiation of contractual provisions at lower levels, under specified conditions) and value 0 if agreements contain no opening clauses).
Source: Own calculation based on data from SES, WIOD, Visser (2016) and Webb (2020).

Table 3S **Estimation results: determinants of wages, additional variable: wage bargaining *(barg3)***

	Software exposure	Robot exposure	AI exposure
	(1)	(2)	(3)
ln_prod	0.098***	0.093***	0.099***
	[0.020]	[0.020]	[0.020]
sex	0.145***	0.167***	0.097***
	[0.005]	[0.005]	[0.005]
ageyoung	-0.142***	-0.148***	-0.132***
	[0.012]	[0.010]	[0.012]
ageaverage	-0.008	-0.014***	-0.008
	[0.006]	[0.005]	[0.006]
loweduc	-0.492***	-0.323***	-0.453***
	[0.017]	[0.013]	[0.021]
mededuc	-0.357***	-0.243***	-0.328***
	[0.013]	[0.011]	[0.016]
full time	0.060***	0.041***	0.035***
	[0.011]	[0.010]	[0.010]
shortdur	-0.303***	-0.270***	-0.290***
	[0.018]	[0.014]	[0.019]
meddur	-0.213***	-0.190***	-0.206***
	[0.011]	[0.010]	[0.011]
longdur	-0.122***	-0.107***	-0.118***
	[0.009]	[0.008]	[0.008]
public	0.038**	0.037**	0.038***
	[0.015]	[0.015]	[0.014]
barg3	0.085***	0.087***	0.100***
	[0.017]	[0.017]	[0.018]
GVC	-0.361**	-0.456***	-0.401***
	[0.150]	[0.127]	[0.154]
Tech	-0.002***	-0.007***	0.004***
	[0.001]	[0.000]	[0.001]
GVCxTech	0.005*	0.007***	0.004*
	[0.003]	[0.002]	[0.002]
R^2	0.82	0.83	0.83
N	4598689	4598689	4598689

Note: Personal and firms' characteristics included as in Table 4C; country and sector fixed effects included; variable barg3 means the predominant level at which wage bargaining takes place, in general: 1: local or company level; 2: industry level; 3: central level.
Source: Own calculation based on data from SES, WIOD, Visser (2016) and Webb (2020).

Table 4S **Estimation results: determinants of wages, additional variable import penetration (import)**

	Software exposure	Robot exposure	AI exposure
	(1)	(2)	(3)
ln_prod	0.098***	0.093***	0.099***
	[0.020]	[0.020]	[0.020]
sex	0.145***	0.167***	0.097***
	[0.005]	[0.005]	[0.005]
ageyoung	-0.142***	-0.148***	-0.132***
	[0.012]	[0.010]	[0.012]
ageaverage	-0.008	-0.014***	-0.008
	[0.006]	[0.005]	[0.006]
loweduc	-0.492***	-0.323***	-0.453***
	[0.017]	[0.013]	[0.021]
mededuc	-0.357***	-0.243***	-0.328***
	[0.013]	[0.011]	[0.016]
full time	0.060***	0.041***	0.035***
	[0.011]	[0.010]	[0.010]
shortdur	-0.303***	-0.270***	-0.290***
	[0.018]	[0.014]	[0.019]
meddur	-0.213***	-0.190***	-0.206***
	[0.011]	[0.010]	[0.011]
longdur	-0.122***	-0.107***	-0.118***
	[0.009]	[0.008]	[0.008]
public	0.038**	0.037**	0.038***
	[0.015]	[0.015]	[0.014]
import	0.157***	0.160***	0.184***
	[0.031]	[0.031]	[0.034]
GVC	-0.361**	-0.456***	-0.401***
	[0.150]	[0.127]	[0.154]
Tech	-0.002***	-0.007***	0.004***
	[0.001]	[0.000]	[0.001]
GVCxTech	0.005*	0.007***	0.004*
	[0.003]	[0.002]	[0.002]
R^2	0.8	0.82	0.81
N	9218140	9218140	9218140

Note: Personal and firms' characteristics included as in Table 4C; country and sector fixed effects included.
Source: Own calculation based on data from SES, WIOD, Webb (2020) and PWT (version 9.1).

Table 5S **Estimation results: determinants of wages, additional variable export penetration (export)**

	Software exposure	Robot exposure	AI exposure
	(1)	(2)	(3)
ln_prod	0.098***	0.093***	0.099***
	[0.020]	[0.020]	[0.020]
sex	0.145***	0.167***	0.097***
	[0.005]	[0.005]	[0.005]
ageyoung	-0.142***	-0.148***	-0.132***
	[0.012]	[0.010]	[0.012]
ageaverage	-0.008	-0.014***	-0.008
	[0.006]	[0.005]	[0.006]
loweduc	-0.492***	-0.323***	-0.453***
	[0.017]	[0.013]	[0.021]
mededuc	-0.357***	-0.243***	-0.328***
	[0.013]	[0.011]	[0.016]
full time	0.060***	0.041***	0.035***
	[0.011]	[0.010]	[0.010]
shortdur	-0.303***	-0.270***	-0.290***
	[0.018]	[0.014]	[0.019]
meddur	-0.213***	-0.190***	-0.206***
	[0.011]	[0.010]	[0.011]
longdur	-0.122***	-0.107***	-0.118***
	[0.009]	[0.008]	[0.008]
public	0.038**	0.037**	0.038***
	[0.015]	[0.015]	[0.014]
export	0.158***	0.161***	0.186***
	[0.031]	[0.032]	[0.034]
GVC	-0.361**	-0.456***	-0.401***
	[0.150]	[0.127]	[0.154]
Tech	-0.002***	-0.007***	0.004***
	[0.001]	[0.000]	[0.001]
GVCxTech	0.005*	0.007***	0.004*
	[0.003]	[0.002]	[0.002]
R^2	0.8	0.82	0.81
N	9218140	9218140	9218140

Note: Personal and firms' characteristics included as in Table 4C; country and sector fixed effects included.
Source: Own calculation based on data from SES, WIOD, Webb (2020) and PWT (version 9.1).

Table 6S **Estimation results: determinants of wages, *GVC* measured by GII (global import intensity of production)**

	Software exposure	Robot exposure	AI exposure
	(1)	(2)	(3)
ln_prod	0.099***	0.093***	0.100***
	[0.020]	[0.020]	[0.020]
sex	0.145***	0.167***	0.096***
	[0.005]	[0.005]	[0.005]
ageyoung	-0.142***	-0.148***	-0.132***
	[0.012]	[0.010]	[0.012]
ageaverage	-0.008	-0.015***	-0.008
	[0.006]	[0.005]	[0.006]
loweduc	-0.492***	-0.322***	-0.452***
	[0.017]	[0.013]	[0.021]
mededuc	-0.357***	-0.243***	-0.327***
	[0.013]	[0.011]	[0.016]
full time	0.061***	0.041***	0.035***
	[0.011]	[0.010]	[0.010]
shortdur	-0.303***	-0.269***	-0.289***
	[0.018]	[0.014]	[0.019]
meddur	-0.213***	-0.190***	-0.206***
	[0.011]	[0.010]	[0.011]
longdur	-0.121***	-0.107***	-0.118***
	[0.009]	[0.008]	[0.008]
public	0.038**	0.036**	0.038***
	[0.015]	[0.015]	[0.014]
GVC	-0.176*	-0.250***	-0.222**
	[0.090]	[0.078]	[0.089]
Tech	-0.002***	-0.007***	0.004***
	[0.001]	[0.000]	[0.001]
GVCxTech	0.002	0.004***	0.003**
	[0.001]	[0.001]	[0.001]
R^2	0.8	0.82	0.81
N	9239722	9239722	9239722

Note: Personal and firms' characteristics included as in Table 4C; country and sector fixed effects included.
Source: Own calculation based on data from SES, WIOD and Webb (2020).

Table 7S **Estimation results: determinants of wages, *Tech* measured by AIOE (AI occupational impact, Felten et al., 2018, 2019)**

	AIOE exposure
	(1)
ln_prod	0.092***
	[0.020]
sex	0.158***
	[0.005]
ageyoung	-0.144***
	[0.010]
ageaverage	-0.014***
	[0.005]
loweduc	-0.308***
	[0.013]
mededuc	-0.237***
	[0.010]
full time	0.032***
	[0.010]
shortdur	-0.265***
	[0.015]
meddur	-0.188***
	[0.010]
longdur	-0.106***
	[0.008]
public	0.038**
	[0.015]
GVC	-0.125
	[0.101]
Tech	0.206***
	[0.013]
GVCxTech	-0.195***
	[0.053]
R^2	0.82
N	9218140

Note: Personal and firms' characteristics included as in Table 4C; country and sector fixed effects included.
Source: Own calculation based on data from SES, WIOD and Felten et al. (2018, 2019).

Table 8S **Estimation results, determinants of job quality EWCS indices, *Tech* measured as software exposure, additional variable coord**

	Dep.var: job quality EWCS indices					
	Social environment	Skills and discretion	Physical environment	Work intensity	Prospects	Working time
ln_prod	0.000	0.000	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
sex	0.029***	0.008	-0.074***	-0.045***	0.018**	-0.083***
	[0.007]	[0.013]	[0.012]	[0.009]	[0.007]	[0.007]
ageyoung	0.003	0.003	-0.078***	0.077***	0.188***	-0.035***
	[0.010]	[0.018]	[0.012]	[0.011]	[0.011]	[0.008]
ageaverage	0.015**	-0.047***	-0.058***	0.075***	0.070***	-0.036***
	[0.007]	[0.012]	[0.008]	[0.008]	[0.007]	[0.006]
loweduc	-0.228***	0.017	-0.171***	-0.092***	-0.055***	0.026**
	[0.013]	[0.020]	[0.019]	[0.015]	[0.011]	[0.011]
mededuc	-0.120***	0.033**	-0.137***	-0.050***	-0.031***	0.013*
	[0.009]	[0.015]	[0.011]	[0.009]	[0.009]	[0.007]
skill1	-0.691***	-0.095***	-0.249***	-0.131***	-0.187***	0.152***
	[0.017]	[0.027]	[0.024]	[0.020]	[0.015]	[0.015]
skill2	-0.502***	-0.070***	-0.174***	-0.053***	-0.124***	0.053***
	[0.013]	[0.019]	[0.020]	[0.013]	[0.011]	[0.012]
skill3	-0.097***	-0.015	-0.001	-0.021	-0.056***	0.078***
	[0.012]	[0.021]	[0.018]	[0.014]	[0.013]	[0.012]
unlimited	0.121***	0.057***	-0.008	0.037***	0.583***	0.033***
	[0.009]	[0.016]	[0.012]	[0.010]	[0.010]	[0.009]
part time	-0.058***	0.004	0.051***	-0.072***	-0.066***	0.110***
	[0.009]	[0.016]	[0.012]	[0.012]	[0.009]	[0.009]
coord	-0.086***	-0.042	0.038*	-0.127***	-0.01	0.116***
	[0.020]	[0.047]	[0.022]	[0.023]	[0.030]	[0.027]
GVC	0.625***	0.322	0.602***	-0.004	0.085	0.332**
	[0.136]	[0.237]	[0.198]	[0.128]	[0.107]	[0.164]
Tech	0.001	0.001	-0.003***	0.001*	0	0
	[0.000]	[0.001]	[0.001]	[0.000]	[0.000]	[0.000]
GVCxTech	-0.013***	-0.002	-0.014***	-0.001	-0.004**	-0.006**
	[0.002]	[0.004]	[0.003]	[0.002]	[0.002]	[0.003]
N	22524	22350	22523	22478	22521	22524

Note: As under Table 1C.
Source: Own calculation based on data from EWCS, WIOD, Visser (2016) and Webb (2020).

Table 9S **Estimation results, determinants of job quality EWCS indices, *Tech* measured as robot exposure, additional variable coord**

	Dep.var: job quality EWCS indices					
	Social environment	Skills and discretion	Physical environment	Work intensity	Prospects	Working time
ln_prod	0.000	0.000	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
sex	0.040***	0.016	-0.062***	-0.045***	0.021***	-0.076***
	[0.008]	[0.013]	[0.012]	[0.010]	[0.007]	[0.007]
ageyoung	0.003	0.002	-0.080***	0.077***	0.188***	-0.036***
	[0.010]	[0.018]	[0.012]	[0.011]	[0.011]	[0.008]
ageaverage	0.015**	-0.047***	-0.057***	0.075***	0.070***	-0.036***
	[0.007]	[0.012]	[0.007]	[0.008]	[0.007]	[0.006]
loweduc	-0.216***	0.021	-0.145***	-0.095***	-0.051***	0.033***
	[0.013]	[0.021]	[0.018]	[0.015]	[0.011]	[0.011]
mededuc	-0.115***	0.035**	-0.125***	-0.051***	-0.030***	0.017**
	[0.009]	[0.015]	[0.011]	[0.009]	[0.009]	[0.007]
skill1	-0.537***	-0.071*	0.198***	-0.180***	-0.150***	0.245***
	[0.023]	[0.039]	[0.040]	[0.028]	[0.020]	[0.022]
skill2	-0.419***	-0.061***	0.086***	-0.083***	-0.103***	0.101***
	[0.016]	[0.023]	[0.026]	[0.016]	[0.013]	[0.013]
skill3	-0.058***	-0.004	0.110***	-0.032**	-0.047***	0.103***
	[0.013]	[0.022]	[0.021]	[0.014]	[0.013]	[0.013]
unlimited	0.121***	0.057***	-0.008	0.037***	0.583***	0.032***
	[0.009]	[0.016]	[0.012]	[0.010]	[0.010]	[0.009]
part time	-0.059***	0.003	0.054***	-0.073***	-0.067***	0.110***
	[0.009]	[0.016]	[0.012]	[0.012]	[0.009]	[0.009]
coord	-0.082***	-0.042	0.044**	-0.130***	-0.009	0.113***
	[0.020]	[0.047]	[0.022]	[0.023]	[0.030]	[0.027]
GVC	0.548***	0.332*	0.559***	-0.129	0.092	0.097
	[0.121]	[0.189]	[0.175]	[0.101]	[0.104]	[0.136]
Tech	-0.001***	0	-0.007***	0.001*	0	-0.002***
	[0.000]	[0.001]	[0.001]	[0.000]	[0.000]	[0.000]
GVCxTech	-0.012***	-0.003	-0.013***	0.002	-0.004***	-0.001
	[0.002]	[0.003]	[0.003]	[0.002]	[0.002]	[0.002]
N	22524	22350	22523	22478	22521	22524

Note: As under Table 1C.
Source: Own calculation based on data from EWCS, WIOD, Visser (2016) and Webb (2020).

Table 10S **Estimation results, determinants of job quality EWCS indices, *Tech* measured as AI exposure, additional variable coord**

	Dep.var: job quality EWCS indices					
	Social environment	Skills and discretion	Physical environment	Work intensity	Prospects	Working time
ln_prod	0.000	0.000	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
sex	0.022***	0.002	-0.085***	-0.045***	0.015**	-0.087***
	[0.007]	[0.013]	[0.012]	[0.009]	[0.008]	[0.007]
ageyoung	0.003	0.003	-0.077***	0.077***	0.188***	-0.035***
	[0.010]	[0.018]	[0.012]	[0.011]	[0.011]	[0.008]
ageaverage	0.014**	-0.047***	-0.059***	0.075***	0.070***	-0.036***
	[0.007]	[0.012]	[0.008]	[0.008]	[0.007]	[0.006]
loweduc	-0.232***	0.015	-0.179***	-0.092***	-0.056***	0.023**
	[0.013]	[0.020]	[0.019]	[0.015]	[0.011]	[0.011]
mededuc	-0.121***	0.031**	-0.138***	-0.050***	-0.031***	0.012*
	[0.009]	[0.015]	[0.011]	[0.009]	[0.009]	[0.007]
skill1	-0.717***	-0.039	-0.444***	-0.092***	-0.189***	0.144***
	[0.020]	[0.029]	[0.029]	[0.021]	[0.017]	[0.019]
skill2	-0.517***	-0.035	-0.284***	-0.031**	-0.125***	0.049***
	[0.016]	[0.022]	[0.024]	[0.014]	[0.013]	[0.016]
skill3	-0.109***	-0.007	-0.061***	-0.013	-0.058***	0.072***
	[0.012]	[0.021]	[0.018]	[0.013]	[0.013]	[0.013]
unlimited	0.121***	0.056***	-0.007	0.036***	0.583***	0.033***
	[0.009]	[0.016]	[0.012]	[0.010]	[0.010]	[0.009]
part time	-0.058***	0.005	0.051***	-0.071***	-0.066***	0.111***
	[0.009]	[0.016]	[0.012]	[0.012]	[0.009]	[0.009]
coord	-0.091***	-0.04	0.029	-0.126***	-0.012	0.113***
	[0.021]	[0.047]	[0.022]	[0.023]	[0.030]	[0.027]
GVC	0.042	0.164	-0.018	0.122	-0.053	0.353***
	[0.147]	[0.253]	[0.166]	[0.131]	[0.115]	[0.125]
Tech	0	0.001*	-0.004***	0.001***	0	0.001*
	[0.001]	[0.001]	[0.001]	[0.000]	[0.000]	[0.000]
GVCxTech	0	0.001	-0.002	-0.003	-0.001	-0.006***
	[0.002]	[0.004]	[0.003]	[0.002]	[0.002]	[0.002]
N	22524	22350	22523	22478	22521	22524

Note: As under Table 1C.
Source: Own calculation based on data from EWCS, WIOD, Visser (2016) and Webb (2020).

Table 11S **Estimation results, determinants of job quality EWCS indices, *Tech* measured as software exposure, additional variable OCG**

	Dep.var: job quality EWCS indices					
	Social environment	Skills and discretion	Physical environment	Work intensity	Prospects	Working time
ln_prod	-0.000*	0.000	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
sex	0.035***	0.018	-0.059***	-0.051***	0.019**	-0.074***
	[0.009]	[0.017]	[0.015]	[0.013]	[0.009]	[0.009]
ageyoung	-0.019*	-0.001	-0.089***	0.072***	0.169***	-0.040***
	[0.012]	[0.022]	[0.015]	[0.016]	[0.014]	[0.010]
ageaverage	0.002	-0.043***	-0.079***	0.083***	0.059***	-0.042***
	[0.008]	[0.015]	[0.009]	[0.010]	[0.009]	[0.007]
loweduc	-0.244***	0.034	-0.194***	-0.106***	-0.044***	0.028**
	[0.017]	[0.025]	[0.025]	[0.020]	[0.014]	[0.014]
mededuc	-0.120***	0.049***	-0.144***	-0.060***	-0.017	0.023***
	[0.011]	[0.019]	[0.015]	[0.011]	[0.012]	[0.009]
skill1	-0.669***	-0.090**	-0.224***	-0.136***	-0.165***	0.174***
	[0.021]	[0.035]	[0.034]	[0.028]	[0.018]	[0.018]
skill2	-0.486***	-0.054**	-0.145***	-0.059***	-0.123***	0.092***
	[0.016]	[0.027]	[0.028]	[0.018]	[0.013]	[0.014]
skill3	-0.079***	-0.014	0.025	-0.024	-0.052***	0.097***
	[0.014]	[0.028]	[0.024]	[0.017]	[0.015]	[0.015]
unlimited	0.114***	0.048**	0.007	0.023*	0.584***	0.037***
	[0.012]	[0.021]	[0.017]	[0.014]	[0.013]	[0.012]
part time	-0.068***	-0.008	0.051***	-0.068***	-0.076***	0.099***
	[0.010]	[0.019]	[0.016]	[0.015]	[0.010]	[0.011]
ocg	-0.188***	0.381***	0.125***	-0.092***	-0.193***	-0.002
	[0.022]	[0.052]	[0.025]	[0.024]	[0.026]	[0.029]
GVC	0.591***	0.181	0.387	0.173	0.188	0.131
	[0.184]	[0.318]	[0.259]	[0.160]	[0.163]	[0.209]
Tech	0	0.001	-0.004***	0.001*	0.001	0
	[0.001]	[0.001]	[0.001]	[0.001]	[0.000]	[0.001]
GVCxTech	-0.013***	0	-0.009**	-0.004	-0.006**	-0.002
	[0.003]	[0.005]	[0.004]	[0.003]	[0.003]	[0.003]
N	14109	13978	14109	14078	14107	14109

Note: As under Table 1C.
Source: Own calculation based on data from EWCS, WIOD, Visser (2016) and Webb (2020).

Table 12S **Estimation results, determinants of job quality EWCS indices, *Tech* measured as robot exposure, additional variable OCG**

	Dep.var: job quality EWCS indices					
	Social environment	Skills and discretion	Physical environment	Work intensity	Prospects	Working time
ln_prod	-0.000*	-0.000**	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
sex	0.035***	0.045***	0.025***	0.018	0.026	0.013
	[0.009]	[0.009]	[0.009]	[0.017]	[0.017]	[0.017]
ageyoung	-0.019*	-0.018	-0.018	-0.001	-0.002	0
	[0.012]	[0.011]	[0.012]	[0.022]	[0.022]	[0.022]
ageaverage	0.002	0.004	0.002	-0.043***	-0.043***	-0.043***
	[0.008]	[0.008]	[0.008]	[0.015]	[0.015]	[0.015]
loweduc	-0.244***	-0.227***	-0.250***	0.034	0.04	0.033
	[0.017]	[0.018]	[0.018]	[0.025]	[0.026]	[0.025]
mededuc	-0.120***	-0.113***	-0.123***	0.049***	0.052***	0.048**
	[0.011]	[0.011]	[0.011]	[0.019]	[0.019]	[0.019]
skill1	-0.669***	-0.494***	-0.700***	-0.090**	-0.051	-0.046
	[0.021]	[0.030]	[0.028]	[0.035]	[0.050]	[0.034]
skill2	-0.486***	-0.391***	-0.502***	-0.054**	-0.038	-0.025
	[0.016]	[0.020]	[0.021]	[0.027]	[0.031]	[0.031]
skill3	-0.079***	-0.035**	-0.093***	-0.014	0.002	-0.007
	[0.014]	[0.015]	[0.015]	[0.028]	[0.029]	[0.027]
unlimited	0.114***	0.115***	0.115***	0.048**	0.048**	0.048**
	[0.012]	[0.012]	[0.012]	[0.021]	[0.021]	[0.021]
part time	-0.068***	-0.069***	-0.067***	-0.008	-0.009	-0.006
	[0.010]	[0.010]	[0.010]	[0.019]	[0.019]	[0.019]
ocg	-0.188***	-0.196***	-0.189***	0.381***	0.383***	0.378***
	[0.022]	[0.023]	[0.023]	[0.052]	[0.052]	[0.052]
GVC	0.591***	0.655***	-0.123	0.181	0.198	0.078
	[0.184]	[0.181]	[0.222]	[0.318]	[0.244]	[0.358]
Tech	0	-0.002**	-0.001	0.001	-0.001	0.001
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
GVCxTech	-0.013***	-0.016***	0.002	0	0	0.002
	[0.003]	[0.003]	[0.003]	[0.005]	[0.004]	
N	14109	14109	14109	13978	13978	13978

Note: As under Table 1C.
Source: Own calculation based on data from EWCS, WIOD, Visser (2016) and Webb (2020).

Table 13S **Estimation results, determinants of job quality EWCS indices, *Tech* measured as AI exposure, additional variable OCG**

	Dep.var: job quality EWCS indices					
	Social environment	Skills and discretion	Physical environment	Work intensity	Prospects	Working time
ln_prod	0.00	0.00	0.00	0.00	0.00	0.00
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
sex	0.025***	0.013	-0.069***	-0.053***	0.015*	-0.076***
	[0.009]	[0.017]	[0.015]	[0.012]	[0.009]	[0.008]
ageyoung	-0.018	0	-0.088***	0.071***	0.169***	-0.040***
	[0.012]	[0.022]	[0.015]	[0.016]	[0.014]	[0.010]
ageaverage	0.002	-0.043***	-0.080***	0.082***	0.059***	-0.042***
	[0.008]	[0.015]	[0.009]	[0.010]	[0.009]	[0.007]
loweduc	-0.250***	0.033	-0.203***	-0.107***	-0.047***	0.027*
	[0.018]	[0.025]	[0.026]	[0.019]	[0.014]	[0.014]
mededuc	-0.123***	0.048**	-0.147***	-0.060***	-0.018	0.023**
	[0.011]	[0.019]	[0.015]	[0.011]	[0.012]	[0.009]
skill1	-0.700***	-0.046	-0.429***	-0.108***	-0.161***	0.167***
	[0.028]	[0.034]	[0.038]	[0.029]	[0.021]	[0.022]
skill2	-0.502***	-0.025	-0.260***	-0.043**	-0.120***	0.089***
	[0.021]	[0.031]	[0.033]	[0.019]	[0.015]	[0.018]
skill3	-0.093***	-0.007	-0.035	-0.018	-0.054***	0.093***
	[0.015]	[0.027]	[0.024]	[0.017]	[0.015]	[0.016]
unlimited	0.115***	0.048**	0.008	0.023*	0.584***	0.037***
	[0.012]	[0.021]	[0.017]	[0.014]	[0.013]	[0.012]
part time	-0.067***	-0.006	0.050***	-0.067***	-0.075***	0.100***
	[0.010]	[0.019]	[0.016]	[0.015]	[0.010]	[0.011]
OCG	-0.189***	0.378***	0.128***	-0.089***	-0.192***	0.001
	[0.023]	[0.052]	[0.026]	[0.025]	[0.026]	[0.028]
GVC	-0.123	0.078	-0.051	0.279	0.044	0.320*
	[0.222]	[0.358]	[0.219]	[0.170]	[0.170]	[0.173]
Tech	-0.001	0.001	-0.005***	0.001**	0	0.001
	[0.001]	[0.001]	[0.001]	[0.001]	[0.000]	[0.001]
GVCxTech	0.002	0.002	0	-0.005**	-0.002	-0.005**
	[0.003]	[0.005]	[0.003]	[0.002]	[0.002]	[0.002]
N	14109	13978	14109	14078	14107	14109

Note: As under Table 1C.
Source: Own calculation based on data from EWCS, WIOD, Visser (2016) and Webb (2020).

Table 14S **Estimation results, determinants of job quality EWCS indices, *Tech* measured as software exposure, additional variable wage bargaining *(barg3)***

	Dep.var: job quality EWCS indices					
	Social environment	Skills and discretion	Physical environment	Work intensity	Prospects	Working time
ln_prod	0.00	0.00	0.00	0.00	0.00	0.00
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
sex	0.029***	0.008	-0.074***	-0.045***	0.018**	-0.083***
	[0.007]	[0.013]	[0.012]	[0.009]	[0.007]	[0.007]
ageyoung	0.003	0.003	-0.078***	0.077***	0.188***	-0.035***
	[0.010]	[0.018]	[0.012]	[0.011]	[0.011]	[0.008]
ageaverage	0.015**	-0.047***	-0.058***	0.075***	0.070***	-0.036***
	[0.007]	[0.012]	[0.008]	[0.008]	[0.007]	[0.006]
loweduc	-0.228***	0.017	-0.171***	-0.092***	-0.055***	0.026**
	[0.013]	[0.020]	[0.019]	[0.015]	[0.011]	[0.011]
mededuc	-0.120***	0.033**	-0.137***	-0.050***	-0.031***	0.013*
	[0.009]	[0.015]	[0.011]	[0.009]	[0.009]	[0.007]
skill1	-0.691***	-0.095***	-0.249***	-0.131***	-0.187***	0.152***
	[0.017]	[0.027]	[0.024]	[0.020]	[0.015]	[0.015]
skill2	-0.502***	-0.070***	-0.174***	-0.053***	-0.124***	0.053***
	[0.013]	[0.019]	[0.020]	[0.013]	[0.011]	[0.012]
skill3	-0.097***	-0.015	-0.001	-0.021	-0.056***	0.078***
	[0.012]	[0.021]	[0.018]	[0.014]	[0.013]	[0.012]
unlimited	0.121***	0.057***	-0.008	0.037***	0.583***	0.033***
	[0.009]	[0.016]	[0.012]	[0.010]	[0.010]	[0.009]
part time	-0.058***	0.004	0.051***	-0.072***	-0.066***	0.110***
	[0.009]	[0.016]	[0.012]	[0.012]	[0.009]	[0.009]
barg	-0.086***	-0.042	0.038*	-0.127***	-0.01	0.116***
	[0.020]	[0.047]	[0.022]	[0.023]	[0.030]	[0.027]
GVC	0.625***	0.322	0.602***	-0.004	0.085	0.332**
	[0.136]	[0.237]	[0.198]	[0.128]	[0.107]	[0.164]
Tech	0.001	0.001	-0.003***	0.001*	0	0
	[0.000]	[0.001]	[0.001]	[0.000]	[0.000]	[0.000]
GVCxTech	-0.013***	-0.002	-0.014***	-0.001	-0.004**	-0.006**
	[0.002]	[0.004]	[0.003]	[0.002]	[0.002]	[0.003]
N	22524	22350	22523	22478	22521	22524

Note: As under Table 1C.
Source: Own calculation based on data from EWCS, WIOD, Visser (2016) and Webb (2020).

Table 15S **Estimation results, determinants of job quality EWCS indices, *Tech* measured as robot exposure, additional variable wage bargaining *(barg)***

	Dep.var: job quality EWCS indices					
	Social environment	Skills and discretion	Physical environment	Work intensity	Prospects	Working time
ln_prod	0.000	0.000	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
sex	0.040***	0.016	-0.062***	-0.045***	0.021***	-0.076***
	[0.008]	[0.013]	[0.012]	[0.010]	[0.007]	[0.007]
ageyoung	0.003	0.002	-0.080***	0.077***	0.188***	-0.036***
	[0.010]	[0.018]	[0.012]	[0.011]	[0.011]	[0.008]
ageaverage	0.015**	-0.047***	-0.057***	0.075***	0.070***	-0.036***
	[0.007]	[0.012]	[0.007]	[0.008]	[0.007]	[0.006]
loweduc	-0.216***	0.021	-0.145***	-0.095***	-0.051***	0.033***
	[0.013]	[0.021]	[0.018]	[0.015]	[0.011]	[0.011]
mededuc	-0.115***	0.035**	-0.125***	-0.051***	-0.030***	0.017**
	[0.009]	[0.015]	[0.011]	[0.009]	[0.009]	[0.007]
skill1	-0.537***	-0.071*	0.198***	-0.180***	-0.150***	0.245***
	[0.023]	[0.039]	[0.040]	[0.028]	[0.020]	[0.022]
skill2	-0.419***	-0.061***	0.086***	-0.083***	-0.103***	0.101***
	[0.016]	[0.023]	[0.026]	[0.016]	[0.013]	[0.013]
skill3	-0.058***	-0.004	0.110***	-0.032**	-0.047***	0.103***
	[0.013]	[0.022]	[0.021]	[0.014]	[0.013]	[0.013]
unlimited	0.121***	0.057***	-0.008	0.037***	0.583***	0.032***
	[0.009]	[0.016]	[0.012]	[0.010]	[0.010]	[0.009]
part time	-0.059***	0.003	0.054***	-0.073***	-0.067***	0.110***
	[0.009]	[0.016]	[0.012]	[0.012]	[0.009]	[0.009]
barg	-0.041***	-0.021	0.022**	-0.065***	-0.004	0.056***
	[0.010]	[0.023]	[0.011]	[0.012]	[0.015]	[0.014]
GVC	0.548***	0.332*	0.559***	-0.129	0.092	0.097
	[0.121]	[0.189]	[0.175]	[0.101]	[0.104]	[0.136]
Tech	-0.001***	0	-0.007***	0.001*	0	-0.002***
	[0.000]	[0.001]	[0.001]	[0.000]	[0.000]	[0.000]
GVCxTech	-0.012***	-0.003	-0.013***	0.002	-0.004***	-0.001
	[0.002]	[0.003]	[0.003]	[0.002]	[0.002]	[0.002]
N	22524	22350	22523	22478	22521	22524

Note: As under Table 1C.
Source: Own calculation based on data from EWCS, WIOD, Visser (2016) and Webb (2020).

Table 16S **Estimation results, determinants of job quality EWCS indices, *Tech* measured as AI exposure, additional variable wage bargaining *(barg)***

	Dep.var: job quality EWCS indices					
	Social environment	Skills and discretion	Physical environment	Work intensity	Prospects	Working time
ln_prod	0.000	0.000	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
sex	0.022***	0.002	-0.085***	-0.045***	0.015**	-0.087***
	[0.007]	[0.013]	[0.012]	[0.009]	[0.008]	[0.007]
ageyoung	0.003	0.003	-0.077***	0.077***	0.188***	-0.035***
	[0.010]	[0.018]	[0.012]	[0.011]	[0.011]	[0.008]
ageaverage	0.014**	-0.047***	-0.059***	0.075***	0.070***	-0.036***
	[0.007]	[0.012]	[0.008]	[0.008]	[0.007]	[0.006]
loweduc	-0.232***	0.015	-0.179***	-0.092***	-0.056***	0.023**
	[0.013]	[0.020]	[0.019]	[0.015]	[0.011]	[0.011]
mededuc	-0.121***	0.031**	-0.138***	-0.050***	-0.031***	0.012*
	[0.009]	[0.015]	[0.011]	[0.009]	[0.009]	[0.007]
skill1	-0.717***	-0.039	-0.444***	-0.092***	-0.189***	0.144***
	[0.020]	[0.029]	[0.029]	[0.021]	[0.017]	[0.019]
skill2	-0.517***	-0.035	-0.284***	-0.031**	-0.125***	0.049***
	[0.016]	[0.022]	[0.024]	[0.014]	[0.013]	[0.016]
skill3	-0.109***	-0.007	-0.061***	-0.013	-0.058***	0.072***
	[0.012]	[0.021]	[0.018]	[0.013]	[0.013]	[0.013]
unlimited	0.121***	0.056***	-0.007	0.036***	0.583***	0.033***
	[0.009]	[0.016]	[0.012]	[0.010]	[0.010]	[0.009]
part time	-0.058***	0.005	0.051***	-0.071***	-0.066***	0.111***
	[0.009]	[0.016]	[0.012]	[0.012]	[0.009]	[0.009]
barg	-0.046***	-0.02	0.015	-0.063***	-0.006	0.057***
	[0.011]	[0.024]	[0.011]	[0.011]	[0.015]	[0.013]
GVC	0.042	0.164	-0.018	0.122	-0.053	0.353***
	[0.147]	[0.253]	[0.166]	[0.131]	[0.115]	[0.125]
Tech	0	0.001*	-0.004***	0.001***	0	0.001*
	[0.001]	[0.001]	[0.001]	[0.000]	[0.000]	[0.000]
GVCxTech	0	0.001	-0.002	-0.003	-0.001	-0.006***
	[0.002]	[0.004]	[0.003]	[0.002]	[0.002]	[0.002]
N	22524	22350	22523	22478	22521	22524

Note: As under Table 1C.
Source: Own calculation based on data from EWCS, WIOD, Visser (2016) and Webb (2020).

Table 17S **Estimation results, determinants of job quality EWCS indices, *Tech* measured as software exposure, GVC measured by GII**

	Dep.var: job quality EWCS indices					
	Social environment	Skills and discretion	Physical environment	Work intensity	Prospects	Working time
ln_prod	0.000	0.000	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
sex	0.030***	0.008	-0.074***	-0.045***	0.018**	-0.083***
	[0.007]	[0.013]	[0.012]	[0.009]	[0.007]	[0.007]
ageyoung	0.003	0.003	-0.078***	0.077***	0.188***	-0.035***
	[0.010]	[0.018]	[0.012]	[0.011]	[0.011]	[0.008]
ageaverage	0.015**	-0.047***	-0.058***	0.075***	0.070***	-0.036***
	[0.007]	[0.012]	[0.008]	[0.008]	[0.007]	[0.006]
loweduc	-0.228***	0.016	-0.170***	-0.091***	-0.055***	0.026**
	[0.013]	[0.020]	[0.019]	[0.015]	[0.011]	[0.011]
mededuc	-0.120***	0.032**	-0.137***	-0.050***	-0.031***	0.013*
	[0.009]	[0.015]	[0.011]	[0.009]	[0.009]	[0.007]
skill1	-0.693***	-0.096***	-0.251***	-0.131***	-0.187***	0.152***
	[0.017]	[0.027]	[0.024]	[0.020]	[0.015]	[0.015]
skill2	-0.503***	-0.070***	-0.174***	-0.054***	-0.123***	0.053***
	[0.013]	[0.019]	[0.020]	[0.013]	[0.011]	[0.012]
skill3	-0.097***	-0.015	-0.001	-0.022	-0.056***	0.078***
	[0.012]	[0.021]	[0.018]	[0.014]	[0.013]	[0.012]
unlimited	0.121***	0.057***	-0.008	0.037***	0.583***	0.032***
	[0.009]	[0.016]	[0.012]	[0.010]	[0.010]	[0.009]
part time	-0.058***	0.005	0.051***	-0.072***	-0.066***	0.110***
	[0.009]	[0.016]	[0.012]	[0.012]	[0.009]	[0.009]
GVC	0.404***	0.247*	0.451***	-0.055	0.047	0.218**
	[0.077]	[0.130]	[0.113]	[0.078]	[0.064]	[0.091]
Tech	0.001*	0.001**	-0.003***	0.001	0	0.001
	[0.000]	[0.001]	[0.001]	[0.001]	[0.000]	[0.000]
GVCxTech	-0.008***	-0.003	-0.010***	0	-0.002**	-0.004***
	[0.001]	[0.002]	[0.002]	[0.001]	[0.001]	[0.001]
N	22554	22380	22553	22508	22551	22554

Note: As under Table 1C.
Source: Own calculation based on data from EWCS, WIOD, Visser (2016) and Webb (2020).

Table 18S **Estimation results, determinants of job quality EWCS indices, *Tech* measured as robot exposure, GVC measured by GII**

	Dep.var: job quality EWCS indices					
	Social environment	Skills and discretion	Physical environment	Work intensity	Prospects	Working time
ln_prod	0.000	0.000	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
sex	0.040***	0.016	-0.062***	-0.045***	0.021***	-0.076***
	[0.008]	[0.013]	[0.012]	[0.010]	[0.007]	[0.007]
ageyoung	0.003	0.002	-0.080***	0.077***	0.188***	-0.036***
	[0.010]	[0.018]	[0.012]	[0.011]	[0.011]	[0.008]
ageaverage	0.015**	-0.047***	-0.057***	0.074***	0.070***	-0.036***
	[0.007]	[0.012]	[0.007]	[0.008]	[0.007]	[0.006]
loweduc	-0.216***	0.02	-0.146***	-0.094***	-0.052***	0.033***
	[0.013]	[0.021]	[0.018]	[0.015]	[0.011]	[0.011]
mededuc	-0.115***	0.034**	-0.125***	-0.051***	-0.030***	0.017**
	[0.009]	[0.015]	[0.011]	[0.009]	[0.009]	[0.007]
skill1	-0.544***	-0.077**	0.191***	-0.178***	-0.152***	0.243***
	[0.023]	[0.039]	[0.040]	[0.028]	[0.020]	[0.022]
skill2	-0.422***	-0.063***	0.083***	-0.082***	-0.104***	0.100***
	[0.016]	[0.023]	[0.026]	[0.016]	[0.013]	[0.013]
skill3	-0.061***	-0.006	0.107***	-0.031**	-0.048***	0.102***
	[0.013]	[0.023]	[0.021]	[0.014]	[0.013]	[0.013]
unlimited	0.120***	0.057***	-0.008	0.037***	0.583***	0.032***
	[0.009]	[0.016]	[0.012]	[0.010]	[0.010]	[0.009]
part time	-0.060***	0.003	0.054***	-0.073***	-0.067***	0.110***
	[0.009]	[0.016]	[0.012]	[0.012]	[0.009]	[0.009]
GVC	0.346***	0.237**	0.372***	-0.124**	0.046	0.083
	[0.065]	[0.111]	[0.095]	[0.063]	[0.061]	[0.078]
Tech	-0.001***	0	-0.007***	0.001	0	-0.001***
	[0.000]	[0.001]	[0.001]	[0.000]	[0.000]	[0.000]
GVCxTech	-0.007***	-0.003*	-0.008***	0.002*	-0.002***	-0.001
	[0.001]	[0.002]	[0.001]	[0.001]	[0.001]	[0.001]
N	22554	22380	22553	22508	22551	22554

Note: As under Table 1C.
Source: Own calculation based on data from EWCS, WIOD, Visser (2016) and Webb (2020).

Table 19S **Estimation results, determinants of job quality EWCS indices, *Tech* measured as AI exposure, GVC measured by GII**

	Dep.var: job quality EWCS indices					
	Social environment	Skills and discretion	Physical environment	Work intensity	Prospects	Working time
ln_prod	0.000	0.000	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
sex	0.022***	0.002	-0.085***	-0.045***	0.016**	-0.086***
	[0.007]	[0.013]	[0.012]	[0.009]	[0.008]	[0.007]
ageyoung	0.003	0.003	-0.077***	0.077***	0.188***	-0.035***
	[0.010]	[0.018]	[0.012]	[0.011]	[0.011]	[0.008]
ageaverage	0.014**	-0.047***	-0.059***	0.075***	0.069***	-0.036***
	[0.007]	[0.012]	[0.008]	[0.008]	[0.007]	[0.006]
loweduc	-0.233***	0.014	-0.179***	-0.091***	-0.056***	0.024**
	[0.013]	[0.020]	[0.019]	[0.015]	[0.011]	[0.011]
mededuc	-0.121***	0.031**	-0.138***	-0.050***	-0.031***	0.013*
	[0.009]	[0.015]	[0.011]	[0.009]	[0.009]	[0.007]
skill1	-0.717***	-0.039	-0.445***	-0.094***	-0.189***	0.144***
	[0.020]	[0.029]	[0.029]	[0.021]	[0.017]	[0.019]
skill2	-0.517***	-0.035	-0.285***	-0.032**	-0.125***	0.049***
	[0.016]	[0.022]	[0.024]	[0.014]	[0.013]	[0.015]
skill3	-0.109***	-0.007	-0.061***	-0.013	-0.058***	0.073***
	[0.012]	[0.021]	[0.018]	[0.013]	[0.013]	[0.013]
unlimited	0.121***	0.056***	-0.007	0.037***	0.583***	0.033***
	[0.009]	[0.016]	[0.012]	[0.010]	[0.010]	[0.009]
part time	-0.058***	0.006	0.052***	-0.071***	-0.066***	0.112***
	[0.009]	[0.016]	[0.012]	[0.012]	[0.009]	[0.009]
GVC	0.037	0.091	0.036	0.06	-0.05	0.197***
	[0.085]	[0.140]	[0.098]	[0.076]	[0.067]	[0.072]
Tech	0	0.001*	-0.004***	0.001***	0	0.001*
	[0.001]	[0.001]	[0.001]	[0.000]	[0.000]	[0.000]
GVCxTech	0	0.001	-0.002	-0.002*	0	-0.003***
	[0.001]	[0.002]	[0.001]	[0.001]	[0.001]	[0.001]
N	22554	22380	22553	22508	22551	22554

Note: As under Table 1C.
Source: Own calculation based on data from EWCS, WIOD, Visser (2016) and Webb (2020).

Table 20S **Estimation results, determinants of job quality EWCS indices, *Tech* measured as software exposure, additional variable import share (import)**

	Dep.var: job quality EWCS indices					
	Social environment	Skills and discretion	Physical environment	Work intensity	Prospects	Working time
ln_prod	0.000	0.000	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
sex	0.029***	0.008	-0.074***	-0.045***	0.018**	-0.083***
	[0.007]	[0.013]	[0.012]	[0.009]	[0.007]	[0.007]
ageyoung	0.003	0.003	-0.078***	0.077***	0.188***	-0.035***
	[0.010]	[0.018]	[0.012]	[0.011]	[0.011]	[0.008]
ageaverage	0.015**	-0.047***	-0.058***	0.075***	0.070***	-0.036***
	[0.007]	[0.012]	[0.008]	[0.008]	[0.007]	[0.006]
loweduc	-0.228***	0.017	-0.171***	-0.092***	-0.055***	0.026**
	[0.013]	[0.020]	[0.019]	[0.015]	[0.011]	[0.011]
mededuc	-0.120***	0.033**	-0.137***	-0.050***	-0.031***	0.013*
	[0.009]	[0.015]	[0.011]	[0.009]	[0.009]	[0.007]
skill1	-0.691***	-0.095***	-0.249***	-0.131***	-0.187***	0.152***
	[0.017]	[0.027]	[0.024]	[0.020]	[0.015]	[0.015]
skill2	-0.502***	-0.070***	-0.174***	-0.053***	-0.124***	0.053***
	[0.013]	[0.019]	[0.020]	[0.013]	[0.011]	[0.012]
skill3	-0.097***	-0.015	-0.001	-0.021	-0.056***	0.078***
	[0.012]	[0.021]	[0.018]	[0.014]	[0.013]	[0.012]
unlimited	0.121***	0.057***	-0.008	0.037***	0.583***	0.033***
	[0.009]	[0.016]	[0.012]	[0.010]	[0.010]	[0.009]
part time	-0.058***	0.004	0.051***	-0.072***	-0.066***	0.110***
	[0.009]	[0.016]	[0.012]	[0.012]	[0.009]	[0.009]
Import	-0.079***	-0.038	0.035*	-0.117***	-0.01	0.106***
	[0.018]	[0.043]	[0.020]	[0.021]	[0.028]	[0.025]
GVC	0.625***	0.322	0.602***	-0.004	0.085	0.332**
	[0.136]	[0.237]	[0.198]	[0.128]	[0.107]	[0.164]
Tech	0.001	0.001	-0.003***	0.001*	0	0
	[0.000]	[0.001]	[0.001]	[0.000]	[0.000]	[0.000]
GVCxTech	-0.013***	-0.002	-0.014***	-0.001	-0.004**	-0.006**
	[0.002]	[0.004]	[0.003]	[0.002]	[0.002]	[0.003]
N	22524	22350	22523	22478	22521	22524

Note: As under Table 1C.
Source: Own calculation based on data from EWCS, WIOD, Visser (2016), Webb (2020) and PWT (version 9.1).

Table 21S **Estimation results, determinants of job quality EWCS indices, *Tech* measured as robot exposure, additional variable import share (import)**

	Dep.var: job quality EWCS indices					
	Social environment	Skills and discretion	Physical environment	Work intensity	Prospects	Working time
ln_prod	0.000	0.000	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
sex	0.040***	0.016	-0.062***	-0.045***	0.021***	-0.076***
	[0.008]	[0.013]	[0.012]	[0.010]	[0.007]	[0.007]
ageyoung	0.003	0.002	-0.080***	0.077***	0.188***	-0.036***
	[0.010]	[0.018]	[0.012]	[0.011]	[0.011]	[0.008]
ageaverage	0.015**	-0.047***	-0.057***	0.075***	0.070***	-0.036***
	[0.007]	[0.012]	[0.007]	[0.008]	[0.007]	[0.006]
loweduc	-0.216***	0.021	-0.145***	-0.095***	-0.051***	0.033***
	[0.013]	[0.021]	[0.018]	[0.015]	[0.011]	[0.011]
mededuc	-0.115***	0.035**	-0.125***	-0.051***	-0.030***	0.017**
	[0.009]	[0.015]	[0.011]	[0.009]	[0.009]	[0.007]
skill1	-0.537***	-0.071*	0.198***	-0.180***	-0.150***	0.245***
	[0.023]	[0.039]	[0.040]	[0.028]	[0.020]	[0.022]
skill2	-0.419***	-0.061***	0.086***	-0.083***	-0.103***	0.101***
	[0.016]	[0.023]	[0.026]	[0.016]	[0.013]	[0.013]
skill3	-0.058***	-0.004	0.110***	-0.032**	-0.047***	0.103***
	[0.013]	[0.022]	[0.021]	[0.014]	[0.013]	[0.013]
unlimited	0.121***	0.057***	-0.008	0.037***	0.583***	0.032***
	[0.009]	[0.016]	[0.012]	[0.010]	[0.010]	[0.009]
part time	-0.059***	0.003	0.054***	-0.073***	-0.067***	0.110***
	[0.009]	[0.016]	[0.012]	[0.012]	[0.009]	[0.009]
Import	-0.076***	-0.038	0.041**	-0.119***	-0.008	0.104***
	[0.018]	[0.043]	[0.020]	[0.022]	[0.028]	[0.025]
GVC	0.548***	0.332*	0.559***	-0.129	0.092	0.097
	[0.121]	[0.189]	[0.175]	[0.101]	[0.104]	[0.136]
Tech	-0.001***	0	-0.007***	0.001*	0	-0.002***
	[0.000]	[0.001]	[0.001]	[0.000]	[0.000]	[0.000]
GVCxTech	-0.012***	-0.003	-0.013***	0.002	-0.004***	-0.001
	[0.002]	[0.003]	[0.003]	[0.002]	[0.002]	[0.002]
N	22524	22350	22523	22478	22521	22524

Note: As under Table 1C.
Source: Own calculation based on data from EWCS, WIOD, Visser (2016), Webb (2020) and PWT (version 9.1).

Table 22S **Estimation results, determinants of job quality EWCS indices, *Tech* measured as AI exposure, additional variable import share (import)**

	Dep.var: job quality EWCS indices					
	Social environment	Skills and discretion	Physical environment	Work intensity	Prospects	Working time
ln_prod	0.000	0.000	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
sex	0.022***	0.002	-0.085***	-0.045***	0.015**	-0.087***
	[0.007]	[0.013]	[0.012]	[0.009]	[0.008]	[0.007]
ageyoung	0.003	0.003	-0.077***	0.077***	0.188***	-0.035***
	[0.010]	[0.018]	[0.012]	[0.011]	[0.011]	[0.008]
ageaverage	0.014**	-0.047***	-0.059***	0.075***	0.070***	-0.036***
	[0.007]	[0.012]	[0.008]	[0.008]	[0.007]	[0.006]
loweduc	-0.232***	0.015	-0.179***	-0.092***	-0.056***	0.023**
	[0.013]	[0.020]	[0.019]	[0.015]	[0.011]	[0.011]
mededuc	-0.121***	0.031**	-0.138***	-0.050***	-0.031***	0.012*
	[0.009]	[0.015]	[0.011]	[0.009]	[0.009]	[0.007]
skill1	-0.717***	-0.039	-0.444***	-0.092***	-0.189***	0.144***
	[0.020]	[0.029]	[0.029]	[0.021]	[0.017]	[0.019]
skill2	-0.517***	-0.035	-0.284***	-0.031**	-0.125***	0.049***
	[0.016]	[0.022]	[0.024]	[0.014]	[0.013]	[0.016]
skill3	-0.109***	-0.007	-0.061***	-0.013	-0.058***	0.072***
	[0.012]	[0.021]	[0.018]	[0.013]	[0.013]	[0.013]
unlimited	0.121***	0.056***	-0.007	0.036***	0.583***	0.033***
	[0.009]	[0.016]	[0.012]	[0.010]	[0.010]	[0.009]
part time	-0.058***	0.005	0.051***	-0.071***	-0.066***	0.111***
	[0.009]	[0.016]	[0.012]	[0.012]	[0.009]	[0.009]
Import	-0.084***	-0.037	0.027	-0.116***	-0.011	0.104***
	[0.019]	[0.043]	[0.020]	[0.021]	[0.028]	[0.025]
GVC	0.042	0.164	-0.018	0.122	-0.053	0.353***
	[0.147]	[0.253]	[0.166]	[0.131]	[0.115]	[0.125]
Tech	0	0.001*	-0.004***	0.001***	0	0.001*
	[0.001]	[0.001]	[0.001]	[0.000]	[0.000]	[0.000]
GVCxTech	0	0.001	-0.002	-0.003	-0.001	-0.006***
	[0.002]	[0.004]	[0.003]	[0.002]	[0.002]	[0.002]
N	22524	22350	22523	22478	22521	22524

Note: As under Table 1C.
Source: Own calculation based on data from EWCS, WIOD, Visser (2016), Webb (2020) and PWT (version 9.1).

Table 23S **Estimation results, determinants of job quality EWCS indices, *Tech* measured as software exposure, additional variable export share (export)**

	Dep.var: job quality EWCS indices					
	Social environment	Skills and discretion	Physical environment	Work intensity	Prospects	Working time
ln_prod	0.000	0.000	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
sex	0.029***	0.008	-0.074***	-0.045***	0.018**	-0.083***
	[0.007]	[0.013]	[0.012]	[0.009]	[0.007]	[0.007]
ageyoung	0.003	0.003	-0.078***	0.077***	0.188***	-0.035***
	[0.010]	[0.018]	[0.012]	[0.011]	[0.011]	[0.008]
ageaverage	0.015**	-0.047***	-0.058***	0.075***	0.070***	-0.036***
	[0.007]	[0.012]	[0.008]	[0.008]	[0.007]	[0.006]
loweduc	-0.228***	0.017	-0.171***	-0.092***	-0.055***	0.026**
	[0.013]	[0.020]	[0.019]	[0.015]	[0.011]	[0.011]
mededuc	-0.120***	0.033**	-0.137***	-0.050***	-0.031***	0.013*
	[0.009]	[0.015]	[0.011]	[0.009]	[0.009]	[0.007]
skill1	-0.691***	-0.095***	-0.249***	-0.131***	-0.187***	0.152***
	[0.017]	[0.027]	[0.024]	[0.020]	[0.015]	[0.015]
skill2	-0.502***	-0.070***	-0.174***	-0.053***	-0.124***	0.053***
	[0.013]	[0.019]	[0.020]	[0.013]	[0.011]	[0.012]
skill3	-0.097***	-0.015	-0.001	-0.021	-0.056***	0.078***
	[0.012]	[0.021]	[0.018]	[0.014]	[0.013]	[0.012]
unlimited	0.121***	0.057***	-0.008	0.037***	0.583***	0.033***
	[0.009]	[0.016]	[0.012]	[0.010]	[0.010]	[0.009]
part time	-0.058***	0.004	0.051***	-0.072***	-0.066***	0.110***
	[0.009]	[0.016]	[0.012]	[0.012]	[0.009]	[0.009]
Export	-0.080***	-0.039	0.036*	-0.118***	-0.01	0.107***
	[0.019]	[0.044]	[0.020]	[0.022]	[0.028]	[0.025]
GVC	0.625***	0.322	0.602***	-0.004	0.085	0.332**
	[0.136]	[0.237]	[0.198]	[0.128]	[0.107]	[0.164]
Tech	0.001	0.001	-0.003***	0.001*	0	0
	[0.000]	[0.001]	[0.001]	[0.000]	[0.000]	[0.000]
GVCxTech	-0.013***	-0.002	-0.014***	-0.001	-0.004**	-0.006**
	[0.002]	[0.004]	[0.003]	[0.002]	[0.002]	[0.003]
N	22524	22350	22523	22478	22521	22524

Note: As under Table 1C.
Source: Own calculation based on data from EWCS, WIOD, Visser (2016), Webb (2020) and PWT (version 9.1).

Table 24S **Estimation results, determinants of job quality EWCS indices, *Tech* measured as robot exposure, additional variable export share (export)**

	Dep.var: job quality EWCS indices					
	Social environment	Skills and discretion	Physical environment	Work intensity	Prospects	Working time
ln_prod	0.000	0.000	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
sex	0.040***	0.016	-0.062***	-0.045***	0.021***	-0.076***
	[0.008]	[0.013]	[0.012]	[0.010]	[0.007]	[0.007]
ageyoung	0.003	0.002	-0.080***	0.077***	0.188***	-0.036***
	[0.010]	[0.018]	[0.012]	[0.011]	[0.011]	[0.008]
ageaverage	0.015**	-0.047***	-0.057***	0.075***	0.070***	-0.036***
	[0.007]	[0.012]	[0.007]	[0.008]	[0.007]	[0.006]
loweduc	-0.216***	0.021	-0.145***	-0.095***	-0.051***	0.033***
	[0.013]	[0.021]	[0.018]	[0.015]	[0.011]	[0.011]
mededuc	-0.115***	0.035**	-0.125***	-0.051***	-0.030***	0.017**
	[0.009]	[0.015]	[0.011]	[0.009]	[0.009]	[0.007]
skill1	-0.537***	-0.071*	0.198***	-0.180***	-0.150***	0.245***
	[0.023]	[0.039]	[0.040]	[0.028]	[0.020]	[0.022]
skill2	-0.419***	-0.061***	0.086***	-0.083***	-0.103***	0.101***
	[0.016]	[0.023]	[0.026]	[0.016]	[0.013]	[0.013]
skill3	-0.058***	-0.004	0.110***	-0.032**	-0.047***	0.103***
	[0.013]	[0.022]	[0.021]	[0.014]	[0.013]	[0.013]
unlimited	0.121***	0.057***	-0.008	0.037***	0.583***	0.032***
	[0.009]	[0.016]	[0.012]	[0.010]	[0.010]	[0.009]
part time	-0.059***	0.003	0.054***	-0.073***	-0.067***	0.110***
	[0.009]	[0.016]	[0.012]	[0.012]	[0.009]	[0.009]
Export	-0.076***	-0.039	0.041**	-0.120***	-0.008	0.105***
	[0.019]	[0.044]	[0.020]	[0.022]	[0.028]	[0.025]
GVC	0.548***	0.332*	0.559***	-0.129	0.092	0.097
	[0.121]	[0.189]	[0.175]	[0.101]	[0.104]	[0.136]
Tech	-0.001***	0	-0.007***	0.001*	0	-0.002***
	[0.000]	[0.001]	[0.001]	[0.000]	[0.000]	[0.000]
GVCxTech	-0.012***	-0.003	-0.013***	0.002	-0.004***	-0.001
	[0.002]	[0.003]	[0.003]	[0.002]	[0.002]	[0.002]
N	22524	22350	22523	22478	22521	22524

Note: As under Table 1C.
Source: Own calculation based on data from EWCS, WIOD, Visser (2016), Webb (2020) and PWT (version 9.1).

Table 25S **Estimation results, determinants of job quality EWCS indices, *Tech* measured as AI exposure, additional variable export share (export)**

	Dep.var: job quality EWCS indices					
	Social environment	Skills and discretion	Physical environment	Work intensity	Prospects	Working time
ln_prod	0.000	0.000	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
sex	0.022***	0.002	-0.085***	-0.045***	0.015**	-0.087***
	[0.007]	[0.013]	[0.012]	[0.009]	[0.008]	[0.007]
ageyoung	0.003	0.003	-0.077***	0.077***	0.188***	-0.035***
	[0.010]	[0.018]	[0.012]	[0.011]	[0.011]	[0.008]
ageaverage	0.014**	-0.047***	-0.059***	0.075***	0.070***	-0.036***
	[0.007]	[0.012]	[0.008]	[0.008]	[0.007]	[0.006]
loweduc	-0.232***	0.015	-0.179***	-0.092***	-0.056***	0.023**
	[0.013]	[0.020]	[0.019]	[0.015]	[0.011]	[0.011]
mededuc	-0.121***	0.031**	-0.138***	-0.050***	-0.031***	0.012*
	[0.009]	[0.015]	[0.011]	[0.009]	[0.009]	[0.007]
skill1	-0.717***	-0.039	-0.444***	-0.092***	-0.189***	0.144***
	[0.020]	[0.029]	[0.029]	[0.021]	[0.017]	[0.019]
skill2	-0.517***	-0.035	-0.284***	-0.031**	-0.125***	0.049***
	[0.016]	[0.022]	[0.024]	[0.014]	[0.013]	[0.016]
skill3	-0.109***	-0.007	-0.061***	-0.013	-0.058***	0.072***
	[0.012]	[0.021]	[0.018]	[0.013]	[0.013]	[0.013]
unlimited	0.121***	0.056***	-0.007	0.036***	0.583***	0.033***
	[0.009]	[0.016]	[0.012]	[0.010]	[0.010]	[0.009]
part time	-0.058***	0.005	0.051***	-0.071***	-0.066***	0.111***
	[0.009]	[0.016]	[0.012]	[0.012]	[0.009]	[0.009]
Export	-0.085***	-0.037	0.027	-0.117***	-0.011	0.105***
	[0.020]	[0.044]	[0.020]	[0.021]	[0.028]	[0.025]
GVC	0.042	0.164	-0.018	0.122	-0.053	0.353***
	[0.147]	[0.253]	[0.166]	[0.131]	[0.115]	[0.125]
Tech	0	0.001*	-0.004***	0.001***	0	0.001*
	[0.001]	[0.001]	[0.001]	[0.000]	[0.000]	[0.000]
GVCxTech	0	0.001	-0.002	-0.003	-0.001	-0.006***
	[0.002]	[0.004]	[0.003]	[0.002]	[0.002]	[0.002]
N	22524	22350	22523	22478	22521	22524

Note: As under Table 1C.
Source: Own calculation based on data from EWCS, WIOD, Visser (2016), Webb (2020) and PWT (version 9.1).

Table 26S **Estimation results, determinants of job quality EWCS indices, *Tech* measured as AIOE exposure**

	Dep.var: job quality EWCS indices					
	Social environment	Skills and discretion	Physical environment	Work intensity	Prospects	Working time
ln_prod	0.000	0.000	0.000	0.000	0.000	-0.000*
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
sex	0.041***	0.024*	-0.066***	-0.044***	0.021***	-0.072***
	[0.008]	[0.013]	[0.011]	[0.010]	[0.007]	[0.007]
ageyoung	0.004	0.001	-0.075***	0.076***	0.188***	-0.035***
	[0.010]	[0.018]	[0.012]	[0.011]	[0.011]	[0.008]
ageaverage	0.016**	-0.047***	-0.056***	0.074***	0.070***	-0.036***
	[0.007]	[0.012]	[0.007]	[0.008]	[0.007]	[0.006]
loweduc	-0.206***	0.03	-0.125***	-0.096***	-0.048***	0.042***
	[0.013]	[0.021]	[0.017]	[0.015]	[0.011]	[0.011]
mededuc	-0.110***	0.040***	-0.114***	-0.052***	-0.028***	0.022***
	[0.009]	[0.015]	[0.010]	[0.009]	[0.009]	[0.007]
skill1	-0.470***	0.023	0.340***	-0.181***	-0.129***	0.326***
	[0.022]	[0.044]	[0.040]	[0.031]	[0.021]	[0.023]
skill2	-0.385***	-0.016	0.166***	-0.084***	-0.093***	0.140***
	[0.014]	[0.025]	[0.024]	[0.017]	[0.013]	[0.013]
skill3	-0.060***	0.015	0.089***	-0.026*	-0.046***	0.111***
	[0.012]	[0.023]	[0.018]	[0.014]	[0.013]	[0.013]
unlimited	0.119***	0.056***	-0.013	0.037***	0.583***	0.031***
	[0.009]	[0.016]	[0.012]	[0.010]	[0.010]	[0.009]
part time	-0.058***	0.004	0.058***	-0.073***	-0.066***	0.112***
	[0.009]	[0.016]	[0.012]	[0.012]	[0.009]	[0.009]
GVC	-0.008	0.215	-0.084	-0.017	-0.116	0.058
	[0.072]	[0.133]	[0.093]	[0.075]	[0.073]	[0.076]
Tech	0.077***	0.054***	0.276***	-0.017	0.016*	0.094***
	[0.012]	[0.020]	[0.018]	[0.012]	[0.010]	[0.012]
GVC xTech	0.251***	-0.024	0.258***	-0.091**	0.092**	-0.07
	[0.050]	[0.075]	[0.062]	[0.043]	[0.041]	[0.051]
N	22524	22350	22523	22478	22521	22524

Note: As under Table 1C.
Source: Own calculation based on data from EWCS, WIOD, Visser (2016) and Felten et al. (2018, 2019).

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