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Working Paper How digital technology affects working conditions in globally fragmented production chains: Evidence from Europe

GUT FME Working Paper Series A, No. 4/2021 (66)

Provided in Cooperation with: Gdańsk University of Technology, Faculty of Management and Economics

Suggested Citation: Parteka, Aleksandra; Wolszczak-Derlacz, Joanna; Nikulin, Dagmara (2021) : How digital technology affects working conditions in globally fragmented production chains: Evidence from Europe, GUT FME Working Paper Series A, No. 4/2021 (66), Gdańsk University of Technology, Faculty of Management and Economics, Gdańsk

This Version is available at: https://hdl.handle.net/10419/273130

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HOW DIGITAL TECHNOLOGY AFFECTS WORKING CONDITIONS IN GLOBALLY FRAGMENTED PRODUCTION CHAINS: EVIDENCE FROM EUROPE

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GUT Faculty of Management and Economics Working Paper Series A (Economics, Management, Statistics) No 4/2021 (66)

November 2021

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HOW DIGITAL TECHNOLOGY AFFECTS WORKING CONDITIONS IN GLOBALLY FRAGMENTED PRODUCTION CHAINS: EVIDENCE FROM EUROPE

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This version: 17 November 2021

Abstract

This paper uses a sample of over 9.5 million workers from 22 European countries to study the intertwined effects of digital technology and crossborder production links on workers' wellbeing. We compare the social effects of technological change exhibited by three types of innovation: computerisation (software), automation (robots) and artificial intelligence (AI). To fully quantify work-related wellbeing, we propose a new methodology that corrects the information on remuneration by reference to such non-monetary factors as the work environment (physical and social), career development prospects, or work intensity. We show that workers' wellbeing depends on the type of technological exposure. Employees in occupations with high software or robots content face worse working conditions than those exposed to AI. The impact of digitalisation on working conditions depends on participation in global production. To demonstrate this, we estimate a set of augmented models for determination of working conditions, interacting technological factors with Global Value Chain participation. GVC intensification is accompanied by deteriorating working conditions - but only in occupations exposed to robots or software, not in AI-intensive jobs. In other words, we find that AI technologies differ from previous waves of technological progress - also in their impact on workers' wellbeing within global production structures.

Keywords: digital technologies, working conditions, GVC, Global Value Chains, artificial intelligence, AI

JEL: F1, F6, J8, O3

1. Introduction

The economic literature has raised many questions in relation to the labour market implications of dynamically changing production systems. Technological progress has triggered a debate on how the substitution of automated processes for human skills affects workers (among countless others: Autor et al., 2003; Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2018, 2020; Frey and Osborne, 2017; Graetz and Michaels, 2018; Brynjolfsson et al., 2018; Goos et al., 2018). Trade with cheap-labour countries raised fears of job loss or downward wage pressure in the developed economies (Autor et al., 2014; Baumgarten et al., 2013; Ebenstein et al., 2014; Egger eat al., 2015; Hummels et al., 2018; Parteka, and Wolszczak-Derlacz, 2020; Shen and Silva; 2018; Cardoso et al., 2021). However, the latest wave of technological progress (including digitalisation, automation and the development of AI: Agrawal et al., 2019; WIPO, 2019; UNIDO, 2020; Gruetzemacher et al., 2021), together with intense cross-country production links within Global Value Chains, GVCs: Baldwin, 2012, 2013; Timmer et al., 2015; Antràs and Chor, 2021), also has another important dimension, namely the impact on working conditions.

Along with the transformation of the task content of jobs (Autor and Handel, 2013; Frey and Osborne, 2017; Acemoglu and Restrepo, 2019; Brynjolfsson and Mitchell, 2017; Brynjolfsson et al., 2018), advanced technology has unquestionably altered the work context or job satisfaction. Some of the changes have been beneficial, such as the use of machines in harmful environments and the automation of dangerous tasks, detecting and reducing the risk of injury (Gisbert et al., 2014). On the detrimental side, modern information technologies and increasing digitisation impact not only on wages and job prospects but also on other aspects of worker satisfaction not directly related to remuneration (Lane and Saint-Martin, 2021). 'Technostress' (the stress provoked by information and communications technology (ICT): Tarafdar et al., 2007; Salanova et al., 2014) affects worker's mental health, productivity, and job satisfaction, with a risk of burnout. Technology affects occupational health and safety (Badri et al., 2018). Many workers face serious work-life conflict due to technology-mediated interruptions and overload, both during and beyond working hours (Berg-Beckhoff et al., 2017).

This paper assesses how progress in digital technology affects working conditions in globally integrated production chains. Our contribution is three-fold. First, while assessing labour conditions, we go beyond the purely monetary approach. The correlation between income and job satisfaction is far from perfect (Clark, 2015), and the socio-economic literature postulates the need to consider non-wage job dimensions in multi-dimensional labour quality analysis (Mira, 2021; Gallie et al. 2012; Fleurbaey, 2015; Nikulin et al, 2021; OECD, 2017). We take a holistic, sociological approach (Ledic and Rubil, 2021) and propose a methodological innovation, i.e.

correcting the wage data according to a series of other factors in job quality: physical and social environment at work, work intensity, the quality of working time, skills and discretion, and prospects.¹

Second, we extend the literature on the implications of technological progress for individual workers by examining different types of digital technology. In particular, we assess how AI technological solutions may differ from previous waves of automation. While the literature on the labour market implications of computerisation and robotisation is abundant (among many others: Acemoglu and Restrepo, 2018, 2020; Goos et al., 2014; Goos, 2018), systematic research dealing explicitly with the impact of AI on workers' well-being is still relatively rare.² This shortcoming is explained in part by the general lack, until recently, of analytical tools to measure AI phenomena, but progress in the quantification of AI solutions for economic and social research (OECD, 2021; Baruffaldi et al., 2020) has now broken new ground for AI-focused labour-market analysis (Lane and San-Martin, 2021; Agraval et al., 2019, Part II). We use the latest measures of the exposure of tasks to software, robots and AI (Webb, 2020) to compare their potentially diverse impact on workers.

Third, we do not isolate the impact of technological progress on workers from changes in business models due to cross-border production fragmentation. The development of digital technologies and GVC are strictly intertwined (Baldwin, 2012, 2016; Basco and Mestieri, 2017). Value chains simply cannot be ignored: half of all world trade takes place within GVCs (World Bank, 2020) and approximately one-fourth of European manufacturing production depends on intermediate products produced in other countries (Parteka and Wolszczak-Derlacz, 2020). The labour market implications of globalised production have been widely examined, but almost always in order to quantify the effects on wages (Baumgarten et al., 2013; Ebenstein et al., 2014; Shen and Silva, 2018; Geishecker and Görg, 2013; Parteka and Wolszczak-Derlacz 2019; 2020; Cardoso et al., 2021; Szymczak and Wolszczak-Derlacz, 2021), jobs and labour demand (Goos et al., 2014; Franssen, 2019; Autor et al., 2014; Egger et al., 2015; Hummels et al., 2018; Szymczak and Wolszczak-Derlacz, 2021), or productivity (Amador and Cabral, 2015). Studies on the social aspects of work within GVCs are less common (Gimet et al. 2015; Milberg and Winkler, 2011; Nikulin et al., 2021), and in many cases deal with problems typical of the developing countries (Delautre et al., 2021; Lee et al., 2016; Nadvi et al., 2004; Rossi, 2013). Surprisingly, the literature on job quality and GVCs has rarely examined the case of European workers (Nikulin et al., 2021); we fill this gap by using a broad European sample.

¹ These features can be quantified via the indicators of the European Working Conditions Surveys (EWCS) (Eurofound, 2021). See Table S2 (in Supplementary materials) for details on job quality indices derived from EWCS and adopted in our analysis.

² Brynjolfsson et al. (2018); Felten et al. (2019) and Webb (2020) assess AI-exposure of jobs.

In short, we propose a multi-country analysis of the link between modern technologies and the well-being of workers in Europe, broadly construed, within a unified micro-level analytical framework. We build a rich employee-level dataset, with information on sociodemographic characteristics, wages, and some non-income aspects of working conditions, as well as GVC- and technology-related features of occupations and industries. The sample encompasses more than 9.5 million manufacturing and service workers in 22 European countries, performing diverse tasks that differ in degree of technology content.

The rest of the paper is structured as follows. In Section 2 we review the literature on the impact of technology on workers, focusing on the effects driven by digital developments. Section 3 presents the data and the main descriptive evidence, concerning the heterogeneity of working conditions in Europe and its relationship with technological exposure. Section 4 presents the econometric results and Section 5 concludes.

2. The effects of digital technology on workers - literature review

In order to see how digital technologies affect working conditions, it is useful to place our own research in the context of the wealth of literature on interactions between technology and labour markets. Unsurprisingly, given the extremely rapid (and unforeseeable Gruetzemacher et al., 2021) technological development of recent decades (Aghion et al., 2019), numerous studies in labour economics have assessed the implications for workers. A vast empirical literature has addressed the common anxiety over wages and/or employment pressure (for a review see Goos, 2018) and technologically driven job displacement: workers performing essentially routine tasks are particularly vulnerable because their jobs are easy to automate (Frey and Osborne, 2017). Consequently, changes in labour demand tend to be "skill biased" because the more skilled workers benefit from the new technologies while the low-skilled can be replaced by them. Such a pattern has been conceptualised through the hypothesis of skill-biased technological change (SBTC) and the related framework of routine-based technological change (RBTC): Acemoglu and Autor (2011); Autor et al. (2003); Goos et al. (2014). Empirical findings confirm this view, pointing towards technology-forced displacement of routine-intensive tasks in many developed countries, particularly the United States (Autor et al., 2003; 2006; Autor and Handel, 2013; Autor and Dorn, 2013; Frey and Osborne, 2017) and Western Europe (the case of the EU-15 has been analysed by Goos et al., 2014 and Marcolin et al., 2016; the case of Germany, by Spitz-Oener, 2006).

These empirical studies on the effects of automation/robotisation typically rely on the classification of workers according to the degree of routine content of the tasks characteristic of

a given occupation. This approach is in line with the view of jobs as a bundle of tasks (Autor et al., 2003) and distinguishes the task-based approach to the study of labour markets from the classic division of workers according to educational level or broad skill category (Acemoglu and Autor, 2011). Indices of occupation-specific routinisation (i.e. routine content of jobs) are available for the US (Autor et al., 2003; Acemoglu and Autor, 2011) and also for broader sets of countries (Marcolin et al., 2016; Lewandowski et al., 2019; Bisello et al., 2021). The recent literature on the AI content of jobs has developed similar metrics, as by combining the information contained in job task descriptions (e.g. from the US Department of Labor's O*NET) with the texts of AI patents (Webb, 2020)³ or by measuring "suitability for machine learning" (Brynjolfsson et al., 2018). Similarly, Felten et al. (2019) propose an AI Occupational Impact measure that matches specific AI applications (image recognition, translation, the ability to play strategic games) with workplace abilities and occupations.

The type of digital technology matters. The application of AI-focused measures to study the labour-market implications of technological progress leads to conclusions different from those postulated by studies on previous technologies. Studies of those technologies underlined the substitution effect between workers and the machines, such as robots (Acemoglu and Restrepo, 2018, 2020). The employment effects of AI are more complex, because some of a given job's tasks may be suitable for machine learning and others not (Brynjolfsson and Mitchell, 2017). Machine learning seems to affect different occupations than earlier waves of automation (Brynjolfsson et al., 2018). It turns out that "AI exposure" is not exactly the same as the danger of being replaced by AI. The workers most exposed to AI might even benefit from the technical capabilities of machine learning and see their work complemented by AI solutions. This is the case of many highly demanding jobs and, paradoxically, high-skilled occupations (chemical engineers, for instance) are among those most exposed to AI (Lane and Saint-Martin, 2021: 23). Webb (2020) examines three different measures of exposure to different types of modern technology: robots, software and artificial intelligence.⁴ He concludes that in contrast to software and robots, AI is targeted at high-skilled tasks. This is because while "robots perform 'muscle' tasks and software performs routine information processing, AI performs tasks that involve detecting patterns, making judgments, and optimization" (Webb, 2020: 3).

The impact of increased adoption of advanced technological solutions (mainly software and ICT) on working conditions has been addressed intensively in the health and safety literature

³ To assess the exposure of occupations to a given technology, Webb (2020) uses the texts of patents to identify the capabilities of a technology, and then measures the extent to which each occupation in the U.S. involves performing similar tasks.

⁴ The distinction between software and AI can be tricky. Conceptually, Webb (2020) considers a computer program to be software (in contrast to AI) if every action it performs has been specified beforehand by a human.

(Badri et al., 2018). Innovative labour risk prevention applications exploiting digital technologies (Gisbert et al., 2014) confirm the potential of these technologies for detecting risk to worker's health and safety in critical environments (e.g. machining, handling and assembly factories). However, the literature also suggests that the impact of the latest technologies on workers' wellbeing is more complex. A major threat to wellbeing is posed by internet addition, "technostress," blurred boundaries between work and personal life and work overload (Tarafdar et al., 2007; Salanova et al., 2014; Berg-Beckhoff et al., 2017). Given that AI technologies are able to automate a wide range of tasks, including non-routine cognitive tasks (Brynjolfsson et al., 2018; Brynjolfsson and Mitchell, 2017), the effects of solutions based on machine learning are likely to be different than in previous waves of automation (ICT or robots), which were targeted at more routine-intensive occupations. A recent OECD study (Lane and Saint-Martin, 2021) points out that AI is likely to change the work environment profoundly by reshaping the content of jobs (transforming occupations), which will affect not only the relations between workers but also human-machine interactions.

Technological progress has also profoundly altered the global structure of production, giving rise to the so-called "second unbundling," which added the international dimension to domestic supply chains typical of the first unbundling (Baldwin, 2012; Baldwin and Venables, 2013): the ICT revolution made it possible to coordinate complexity at a distance and to offshore labour-intensive manufacturing stages to remote countries with lower labour costs. While offshoring was viewed as the successor to industrial revolution (Blinder, 2006), the third unbundling of globalisation, driven by such solutions as telerobotics or telepresence (enabling workers in one country to perform service tasks in another), is the perspective that is now gaining traction (Baldwin, 2016). Further development of AI technologies may open up completely new possibilities, difficult indeed to forecast (Gruetzemacher et al., 2021).

The labour market effects of GVC differ from the pressure due to traditional trade, where production processes do not cross national borders (Szymczak and Wolszczak-Derlacz, 2021). Numerous studies have assessed the labour market effects of production fragmentation (offshoring) in conjunction with the impact of technology - mainly by identifying which categories of workers are most endangered due to the type of tasks they perform (Baumgarten et al., 2013; Ebenstein et al., 2014; Shen and Silva, 2018; Goos et al., 2014; Parteka and Wolszczak-Derlacz 2019; 2020; Autor et al., 2015; Egger et al., 2015; Hummels et al., 2018). Unsurprisingly, occupations consisting mainly in repetitive (routine-intensive) tasks are more susceptible to be displaced or to be subjected to downward wage pressure. The effects of trade and automation are intertwined: measures of offshorability (Blinder, 2009; Blinder and Krueger, 2013) are

strongly related to the degree of job routinisation (Autor et al, 2003; Autor and Handel, 2013) and probability of computerisation (Frey and Osborne, 2017). However, the literature focusing explicitly on working conditions broadly understood (not just wages or number of jobs), and the way they are jointly affected by the development of digital (especially AI) technologies and GVC proliferation, is missing. In the next section we describe how we intend to fill this gap.

3. Methodological setting and descriptive evidence

3.1 Dataset

For the purpose of our analysis we build a rich employee-level dataset, containing information of workers' socio-demographic characteristics, wages, several aspects of working conditions, and GVC- and technology-related features of occupations/industries. The analysis covers more than 9.5 million workers in 22 European countries observed around 2015.⁵ The Appendix contains the list of countries (Table 1A) and industries (Table 2A), and the Supplementary materials describe the original data sources (Table S1), namely: SES (Structure of Earnings Survey - 2014),⁶ EWCS (European Working Conditions Survey - 2015) and WIOD (World Input Output Database - 2016).

The quantification of exposure to digital technologies is performed at two levels. First, we employ the digital taxonomy of industries from Van Ark et al. (2019), dividing sectors into digital producing and (least or most) digital intensive using categories⁷ (Table 2A). Secondly, we combine the micro-level information contained in SES and EWCS with three alternative indices used to classify workers according to the digital exposure of their jobs to software, robots and AI (Webb, 2020).⁸ The data is then combined at the occupation level corresponding to two-digit ISCO-08 code (this level of aggregation reflects the level of detail in EWCS). The conversion from Webb's list of occupations to our ISCO-08 codes was performed by using first his

⁵ This date reflects the availability of data on working conditions: the EWCS survey is conducted every five years, the latest wave is for 2015 (EWCS 2020 field work has been halted due to COVID).

⁶ Access to the micro-level Structure of Earnings Survey (SES) data is free of charge, but an application is required. The data was granted by Eurostat upon acceptance of a research proposal (Proposal 225/2016-EU-SILC-SES).

⁷ The classification of Van Ark et al. (2019) draws upon Calvino et al. (2018) and is based on such aspects as: the share of tangible and intangible ICT investment; the share of intermediate purchases of ICT goods and services; the stock of robots per hundred employees; the share of ICT specialists in total employment; and the share of turnover from online sales. In particular, Van Ark et al. (2019) separate out: electrical and optical equipment, publishing, audio-visual and broadcasting activities, telecom services and IT and other information services, classifying them as "producing digital goods and services" (DP). The earlier taxonomy of Van Ark et al. (2016) is based only on ICT service and investment intensity.

⁸ Alternative classifications of occupations according to their AI content have been proposed by Brynjolfsson et al. (2018) and Felten et al. (2019). We rely on the classification of Webb (2020) because it allows us to confront different technologies: software, robots and AI. Webb's occupational exposure scores for a given technology t (computers, robots, AI) express the intensity of patenting activity in technology t directed towards the tasks in that occupation.

crosswalk (occ1990dd) from O*NET, and then the Bureau of Labor Statistics' crosswalk from O*NET to ISCO_08.

The quantification of working conditions is no easy task. To fully account for the complexity of work satisfaction and its non-wage dimensions (in line with Ledić and Rubil, 2021), we correct the wage data using non-wage aspects through the combination of EWCS and SES data.⁹ We proxy the working conditions (*WC*) faced by every worker in the dataset by:

$$WC_{io}^{k} = wage_{i} \times \frac{JQ_{oc}^{k}}{\frac{\sum_{i=1}^{N_{c}} JQ_{oc}^{k}}{N_{c}}}$$
(1)

where: JQ is job quality index of type k (derived from EWCS) typical for occupation o in country c and wage_i is the hourly wage of worker i (data from SES). The set of k aspects of job quality includes: physical environment, work intensity, working time quality, social environment, skills and discretion, and prospects - see Table S2 in Supplementary materials for details on the exact content and method of quantification. N_c denotes the total number of workers in country c. WC is thus obtained by multiplying the wage (in US dollars) by the job quality index (relative to the country mean). Such a composite measure can be higher (or lower) than the original (monetary) wage, depending on whether an individual performs a job of higher (lower) quality than other workers in the same country. For example, if a worker is employed in an occupation characterised by a social environment 10% better than the country average (based on survey results), we assume that her/his working conditions (taking account of both monetary remuneration and social environment) are 10% better than would be due purely to wages.

Finally, to capture the extent of involvement in globally fragmented production, we use industry-level indicators of GVC (based on WIOD input-output data, Timmer et al., 2015), matched with the rest of the data according to the sector of activity (NACE Rev. 2).¹⁰ In the benchmark analysis, GVC intensity is measured by the share of foreign value added in exports (FVA/Export), obtained from the decomposition of gross exports (Wang et al. 2013). That is, GVC intensity measures the value added derived from imported inputs, used in the production of goods or services (intermediate or final) and then exported. Alternative measures of GVC (*OFF*: classic offshoring, i.e. the ratio of intermediate imports to total sectoral output, Feenstra and Hanson, 1999; or *GII* - global import intensity of production, Timmer et al., 2016; Szymczak et al., 2021) are adopted for the robustness analysis.

⁹ Such an approach is also supported by the examination of the correlation matrix between separate job quality indicators and wages (Table 3A in the Appendix): JQ indices are loosely related to wages (see the column in grey): this is especially so for such aspects of job quality as social environment and working time quality, and, to a lesser extent, physical environment and work intensity.

¹⁰ In some cases we had to combine the original WIOD sectors into broader categories (listed in Table 2A), to assure their correspondence with the sectoral information present in SES. For such industry groupings, we computed an average of underlying industries' GVC measures (e.g. share of foreign value added in exports).

3.2 Job quality in Europe - variation across countries and occupations

Job quality varies both between and within countries in Europe: the boxplots in Figure 1 illustrate cross-country variability in the original job quality indices from EWCS. On average, the best social environment at work is found in Portugal and Bulgaria, the worst in France and the Slovak Republic. In Portugal, physical environment and working time quality are ranked relatively high compared to the other countries. Bulgaria has the lowest work intensity, while this indicator is relatively high in Romania and Cyprus (implying a negative impact on workers' wellbeing in those countries). Regarding the physical environment, the highest average scores are recorded in the Czech Republic, Portugal and Belgium, the lowest in Romania, France and Spain. As to prospects, a concept that comprises job security as well as future career perspectives, the worst scores are registered in Cyprus and Italy, the best in Luxembourg and Norway. Importantly, Figure 1 also illustrates the considerable within-country dispersion in job quality indices - a sign that a more detailed analysis (accounting for occupational and worker-level heterogeneity) is needed.

[Figure 1 about here]

In terms of variation across occupations, the pattern is rather clear. Figure 2 shows that lowlevel workers, plant and machine operators, assemblers, as well as agricultural and fishery workers, face the worst working conditions in terms of skills, discretion and prospects. Unsurprisingly, the worst physical environment is faced by craft and related trades workers, plant and machine operators, and assemblers. Managers and professionals benefit from the highest level of prospects, skills and discretion, but their work intensity is also high.

[Figure 2 about here]

4.3. Job quality versus technological exposure and GVC involvement

Our database allows us to examine the relationship between alternative indices of job quality from EWCS and the different types of technology used intensively in the job. Figure 3 shows the correlation of occupational exposure to software, robots and AI (Webb, 2020) with various nonwage aspects of job quality. Greater exposure to all three types of technology is correlated positively with the quality of the social environment (Figure 3, panel A), and negatively with physical environment (Figure 3, panel C) and work intensity (Figure 3, panel D). Overall, greater exposure to AI is accompanied by better prospects and higher levels of skills and discretion, but also greater work intensity and a poorer physical environment. For some aspects of job quality, however, correlations differ between exposure to AI technologies and exposure to computerisation or robotisation. For instance, skills and discretion (Figure 3, panel B) and prospects (Figure 3, panel E) are correlated negatively with robot/software exposure but positively with AI exposure. This suggests that the connection between working conditions and digitalisation of the work environment depends on the specific type of technology installed in a given occupation.

[Figure 3 about here]

Given that our analysis combines trends in technology and changes in the global structure of production, we also track the relationship between various aspects of job quality and involvement in GVCs (Figure 4). Apart from social environment and prospects, the other dimensions of job quality tend to be negatively correlated with GVC intensity. In other words, some aspects of quality for European workers (such as skills and discretion, physical environment, and work intensity) may be worse in the sectors more heavily involved in globally fragmented value chains. Figures 3-4 show simple unconditional correlation plots, which should serve as a starting point for more in-depth econometric analysis of the determinants of multidimensional workers' well-being, conditional upon specific worker or industry characteristics and involving the interplay between digital technologies and GVCs.

[Figure 4 about here]

4. The relationship between digital technologies and working conditions: econometric analysis

4.1 The models

To estimate the role of alternative factors in determining the working conditions of European workers, we employ econometric modelling techniques taking account of the multidimensional nature of the dependent variable (eq. 1) and mechanisms of impact at different levels (worker, occupation, sector/industry). Methodologically, we adopt a procedure akin to that of Nikulin et al. (2021) or Budria and Milgram Baleix (2020) based on merging micro-level labour market outcomes (here, working conditions), micro-level explanatory variables (features of individuals and firms), and sector-specific characteristics (productivity, digital technology, GVC intensity). The summary statistics of all the variables are presented in Table 4A in the Appendix.

To begin with, we estimate a regression model derived from the augmented Mincer earnings function (reviewed in Heckman et al., 2006), where GVC and technology are treated separately. The relationship between digital technologies and working conditions is first assessed using the sectoral dimension (model 2a), then enriched with data on occupation-specific technological exposure (model 2b):

$$ln(WC_{ijsc}^{k}) = \alpha + \beta_1 Worker_i + \beta_2 Firm_j + \beta_3 lnProd_{sc} + \beta_4 GVC_{sc} + \beta_5 Tech_s + D_c + D_s + \varepsilon_{ijsc}$$
(2a)

$$ln(WC_{io\,isc}^{k}) = \alpha + \beta_1 Worker_i + \beta_2 Firm_i + \beta_3 lnProd_{sc} + \beta_4 GVC_{sc} + \beta_5 Tech_o + D_c + D_s + \varepsilon_{io\,isc},$$
(2b)

where: i = worker; e = occupation, j = firm, s = sector of employment, $e = \text{country and } k = \text{the particular aspect of job quality captured in our working conditions measure (eq.1). The log of the working conditions is regressed on: the vector of individual characteristics ($ *Worker*), namely sex, age, education, type of employment (a binary variable, full-time/part time); firm characteristics (*Firm:*length of service in the enterprise, form of economic and financial control: public/private), industry productivity (*InProd*: the log of the ratio of value added to total hours worked); and, finally, our main variable of interest:*Tech*. Dependence on digital technologies is measured either at sector level (eq. 2a) or occupation level (eq. 2b). Specifically, in eq. (2a)*Tech* $, <math>= \{Tech^{IDIU}, Tech^{MDIU}, Tech^{DP}\}$ follows the taxonomy of Van Ark et al., 2019 (Table 2A) while in eq. (2b) *Tech*, $= \{Tech^{Tothure}, Tech^{robot}, Tech^{AI}\}$ is captured via degree of exposure to software, robots or AI (Webb, 2020). To address the omitted-variables bias, we include country and sector fixed effects: D_e gauges all country-specific characteristics, such as labour market regulation,¹¹ while D_s captures the remaining characteristics of sectors.

In models (2a) and (2b), *GVC* (i.e. FVA/exports - Wang et al. 2013) is included to check whether working conditions tend to be better or worse for workers in sectors more heavily involved in global production fragmentation (Nikulin et al., 2021). However, considering that technological progress and the topography of GVCs are intertwined (Baldwin, 2012; 2016; Baldwin and Venables, 2013), we augment the basic models with interactions between *GVC* and *Tech* – measured at sectoral or occupational level (eq. 3a and eq. 3b respectively):

$$\begin{aligned} \ln(WC_{ijsc}^{k}) &= \alpha + \beta_{1}Worker_{i} + \beta_{2}Firm_{j} + \beta_{3}lnProd_{sc} + \beta_{4}GVC_{sc} + \beta_{5}Tech_{s} + \beta_{6}GVC_{sc} \times Tech_{s} + D_{c} + \\ D_{s} + \varepsilon_{ijsc}. \end{aligned}$$
(3a)
$$ln(WC_{iojsc}^{k}) &= \alpha + \beta_{1}Worker_{i} + \beta_{2}Firm_{j} + \beta_{ln3}Prod_{sc} + \beta_{4}GVC_{sc} + \beta_{5}Tech_{o} + \beta_{6}GVC_{sc} \times Tech_{o} + D_{c} + \\ D_{s} + \varepsilon_{iojsc}. \end{aligned}$$
(3b)

The marginal effect of digital technology exposure on working conditions is equal to $\frac{\delta WC}{\delta Tech_s} = \beta_5 + \beta_6 GVC$ in eq. (3a) and $\frac{\delta WC}{\delta Tech_o} = \beta_5 + \beta_6 GVC$ in eq. (3b). The interactions help to determine whether the impact of digital technologies on working conditions is conditional upon the intensity of involvement into GVC.

¹¹ The supplementary materials provide robustness check estimates, augmenting the model by specific variables on labour market institutions and trade openness.

4.2 The estimation results¹²

Our reading of the results begins with digital technology captured at the sectoral level. Table 1 presents the results for separate estimations for six different aspects of job quality, captured in our composite measure of working conditions. For the sake of clarity, here we present only the key variables – *Tech* and *GVC* – but all the models incorporate all the other control variables (as indicated in eq. 2a; the complete results are reported in the Supplementary materials (Table S3).¹³ By sector, we find that working conditions are worse in sectors marked by intensive use of digital technology, designated MDIU (more digital-intensive use, as against LDIU, less digital-intensive use, the model's default/missing category). This result holds for all aspects of workers' wellbeing. However, the sectors where digital technologies are actually produced (category DP – digital producing) are different: in them, such aspects of job quality as skills and discretion or physical environment are better than in LDIU. This result suggests an interesting initial conclusion: namely that the wellbeing of workers in sectors using digital technologies differs from that of those in the sectors that produce them.

Additionally, we find that almost all aspects of working conditions (apart from social environment) tend to be worse in sectors more heavily involved in GVC (Table 1). To check whether this result depends on technology exposure, we can consider the results for the interaction between Tech, and GVC (Table 2 and Table S4 with a full set of covariates). Figure 5 illustrates the main results: predicted working conditions (adjusted by the six job quality indices) are plotted against GVC for sectors grouped into digital technology using (MDIU, LDIU) and digital technology producing (DP) categories. Figure 5 should be interpreted as follows: three lines correspond to the three types of sector (LDIU, MDIU, DP). The vertical position of each line reflects the general level of a specific working condition; for example, at low GVC intensity the best working conditions (no matter which job quality aspect is considered) are in DP and the worst in MDIU. The slope of the lines illustrates how working conditions change as participation in GVC increases (i.e. as the share of FVA increases). Generally, working conditions tend to worsen along with increasing participation in GVC in the DP and, to a lesser extent, the LDIU sectors. For the digital intensive-using sectors (MDIU), however, working conditions do not change greatly: there is only a slight deterioration in the work intensity, prospects and working time quality.

¹² Models (2a, 2b) and (3a, 3b) are estimated using weighted regression with robust standard errors clustered at the firm level. The weights are based on the rescaled SES grossing up factor adjusted for number of observations per country (so each country is equally represented in the sample).

¹³ Ceteris paribus, male, older, better educated, full-time workers, with permanent contracts and longer tenure in the enterprise enjoy better working conditions. Given that monetary wage is a component of the dependent variable, these results are in line with the Mincerian theory of wage determination (reviewed in Heckman et al., 2006).

[Table 1 about here] [Table 2 about here] [Figure 5 about here]

Let us now consider the results when technology is measured at occupation level (eq. 2b and 3b). Our key results refer to *Tech*₀ estimates, controlling for all the other worker and firm characteristics (full set of results in Tables S5–S7). There is a statistically significant negative correlation between working conditions and technology for the occupations most exposed to software and robots (note the coefficients obtained for *Tech*₀). At the same time, conditions tend to be better in AI-exposed occupations (i.e. when *Tech*₀ is measured via AI exposure - Table 3, panel C). As in the previous estimates, employees in the more GVC-intensive sectors face worse working conditions.

[Table 3 about here]

Does the relationship between technology and working conditions depend on the extent of involvement in global production sharing? Statistically significant estimates of β_6 of the augmented model, with interactions (results reported in Table 4, illustrated in Figures 6A-6C), indicate that this is indeed the case. In particular, Figure 6 plots predicted working conditions for three levels of technological exposure (low, medium, high¹⁴) against *GVC*, considering our three types of technology – software (panel 6A), robots (panel 6B), AI (panel 6C). Figure 6A shows that working conditions are on average worse in jobs with high software exposure and low GVC intensity. However, as GVC intensity increases, the situation changes, and trends vary with degree of software exposure and specific aspect of job quality. For occupations with low software exposure, working conditions tend to worsen as GVC involvement intensifies (but for skills and discretion and the physical environment, the changes are negligible. For those with high software exposure, however, the conditions capturing social environment and prospects improve as GVC increases, while the other aspects of workers' wellbeing deteriorate.

Figure 6B refers to robot technology, Figure 6C to AI. On average, all the aspects of working conditions are better in jobs with relatively low robot exposure. However, they tend to deteriorate as GVC increases. The trend is different for jobs with high robot exposure: here some aspects of working conditions improve as GVC intensifies (except for work intensity, skill and discretion, and physical environment, the latter two not reacting significantly).

Importantly, however, when technological content is measured by AI exposure, the situation is different (Figure 6C). Generally, workers more exposed to AI tend to enjoy better

¹⁴Low tech exposure: tech =10, medium tech exposure: tech =40, high tech exposure: tech =80.

working conditions, and these conditions do not change greatly with increasing GVC involvement. This finding is in line with the literature on the impact of the latest digital technologies on labour markets: Felten et al. (2019) actually find that AI-exposed occupations experience a positive, if minor, change in wages.

[Table 4 about here] [Figure 6 about here]

4.3. Robustness checks and extensions

In order to check the sensitivity of our results, we run a number of robustness tests. First we use an alternative technological classification of sectors, applying the digital industry taxonomy of Van Ark et al. (2016), which divides sectors into: less ICT intensive using (LIIU), more ICT intensive using (MIIU) and ICT producing (IP). Repeated estimations of eq. 2a and eq. 3a (Table S8 and Table S9 in Supplementary materials) confirm our baseline results: the difference between working conditions in the sectors that use and produce digital (or ICT) technologies, with generally better conditions for workers in the technology producing industries, and the intertwined effects of technology and GVC involvement on workers' wellbeing.

Given that our analysis is based on data for workers in many European countries, we extend the analysis by considering possible national heterogeneity and adding country-level controls. We re-estimate all versions of the baseline model with technology measured at sectoral and at occupational level (results in Supplementary materials, Tables S10-S21). We start by considering cross-country differences in labour market institutional coordination, i.e. the variability of wage-bargaining schemes. The data is derived from the Database on Institutional Characteristics of Trade Unions, Wage Setting, State Intervention and Social Pacts (ICTWSS, Visser, 2019). We consider the recoded variable of coordination of wage-setting (Coord) where 1 denotes centralised or industry-level bargaining, 0 mixed industry and firm-level bargaining¹⁵ (Tables S10-S13). Alternatively, we employ a composite index of multi-level bargaining: the higher the index, the more centralised the bargaining scheme (Tables S14-S17). Next, we consider the general degree of trade openness measured via the share of exports (or imports) in GDP; these variables also help to verify whether the GVC measures in the baseline models succeed in capturing the overall effects of trade integration (Tables S18-S21). Neither augmenting the regression by variables for country-specific wage-setting mechanisms nor by variables for openness alters the baseline results.

¹⁵ We take into account the recoded variable of the coordination of wage-setting (*Coord*) where 1 denotes centralized or industry-level bargaining (BE, DE, ES, IT, LU, NL, NO, SE) while 0 is for the countries with mixed industry and firm-level bargaining (BG, CY, CZ, EE, FR, HU, LT, LV, MT, PL, PR, RO, SK, UK).

Finally, to confirm the robustness of the results on the role of production-sharing intensity, we alter the way in which it is measured. That is, we replace our benchmark GVC measure (FVA/exports) by a traditional offshoring index, *OFF* (the ratio of imported intermediates to total sectoral output, Feenstra and Hanson, 1999) or by the global import intensity of production (*GII*) defined by Timmer et al. (2016) and recently used in Szymczak et al. (2021) who describe the procedure for calculating *GII*. *GII* is based on the ratio of the sum of all intermediate imports along the entire chain for the final product (not only for the immediately preceding stage, as in *OFF*), divided by the value of the final product. Our main results for GVC hold: greater involvement in global structures of production correlates negatively with working conditions, and this effect depends on technology exposure (see Tables S22-S29). We find only minor change in the statistical significance of the second-best production-sharing variables.

5. Conclusions

The dynamic development of digital technologies, combined with changes in the structure of production and its international fragmentation, are affecting the lives of workers worldwide. Our analysis here focuses on an issue that has been relatively little studied in the socio-economic literature: non-wage working conditions. In particular, we have examined the intertwined effects of digital technologies (ICT, robots, and also more complex AI solutions) and cross-border production links on workers' wellbeing.

For the purpose of this analysis we have constructed a rich dataset, merging worker-level information on socio-demographic characteristics, wages, and several non-income aspects of job quality, as well as GVC- and technology-related features. For a large sample (more than 9.5 million workers in 22 European countries), we provide evidence that is neither country- nor industry-specific. At the same time, we capture individual-, occupation-, sector- and country-level heterogeneity with a wide array of control variables at all these levels. As to working conditions, the relevant factors go beyond pure monetary remuneration, in a holistic approach rooted in the sociological literature and capturing a series of non-income aspects of jobs: the physical and social environment at work, work intensity, working time quality, skills and discretion, and prospects.

We assess the impact of digitalisation at two levels: sectoral and occupational, analysing at the same time how technological developments interact with the pressure exerted by the fragmentation of production. Hence, in line with the globalisation literature (Baldwin, 2012, 2016; Antràs and Chor, 2021) we do not isolate the worker-level impact of technological progress from changes in business models owing to the intensification of global value chains. The estimates of a set of augmented models for the determination of working conditions, interacting technological and GVC forces, suggest several conclusions.

First, the effects of technology and GVC participation are in fact intertwined and should not be analysed separately. In general, employees in the more GVC-intensive and digital technology-using sectors tend to face worse working conditions. Workers' wellbeing definitely differs between the industries that *use* digital technologies and those that *produce* them. However, the impact of digitisation on working conditions is conditional on the degree of involvement in global value chains. At low levels of GVC intensity, the worst working conditions are found in the sectors most intensive in the use of digital technology; the best, in the industries that produce it. GVC intensification is accompanied by deteriorating working conditions – but chiefly in the sectors where they were relatively good at the outset. As a result, at high levels of GVC involvement, the differences in working conditions between sectors are less pronounced than where production is not as globally integrated. In other words, the intensification of cross-border production fragmentation produces a convergence in working conditions between sectors of different technological content.

Second, we reveal that the way in which digital technology affects working conditions depends on the specific *type of* technology. Much of the literature to date has focused on the impact of ICT on workers. We provide evidence of interesting differences between the impact of AI and that of ICT (software) or robot technology. Workers whose occupations are particularly exposed to software and robots are worse off, while in AI-exposed jobs they tend to improve. This finding is in line with the recent evidence that AI technologies are indeed unique – in particular, unlike software and robotics, AI is targeted at high-skilled tasks (Brynjolfsson et al., 2018; Brynjolfsson and Mitchell, 2017; Webb, 2020; Lane and Saint-Martin, 2021). We also find that, in contrast to jobs exposed to software or robots, working conditions in AI-exposed occupations (i.e. jobs with a relatively high content of AI technology) do not worsen as GVC involvement intensifies.

Additional extensions of our analysis could involve the development of more detailed measures of the digital content of sectors and jobs. Further, once new EWCS indices are available (based on surveys done in the Covid era), they could be used to investigate whether more intense use of digital technologies (owing, say, to emergency-imposed remote working) has affected workers' well-being (in such areas as work-life balance, satisfaction from the social and physical environment, and so on). Another possible avenue of research relates to gender differences in working conditions and their technological determinants (bearing in mind that the structure of employment in technology-intensive sectors and occupations tends to be genderunequal). Finally, given rapidly changing working relations (including on-demand job and platform work), an analysis of wellbeing by type of employment contact could afford important additional insights into job quality.

Funding and Acknowledgement: All three authors contributed to the study conceptualisation and design. Aleksandra Parteka was responsible for the research on technological specialisation, which was supported by the National Science Centre, Poland (grant number: 2020/37/B/HS4/01302). Joanna Wolszczak-Derlacz was responsible for the research on GVCs, which was supported by the National Science Centre, Poland (grant number: 2015/19/B/HS4/02884). Dagmara Nikulin was responsible for the research based on working conditions data. We are also grateful for the support of the European Trade Union Institute and the insightful comments of their members on the research results underlying this paper.

References

Acemoglu, D. and Autor, D. H. (2011). Skills, Tasks and Technologies: Implications for Employment and Earnings, in: O. Ashenfelter and D.E. Card (eds.) *Handbook of Labor Economics*, Vol. 4B, Amsterdam: Elsevier, pp. 1043-1171.

Acemoglu, D., and Restrepo, P. (2018). The race between man and machine: Implications of technology for growth, factor shares, and employment. *American Economic Review*, 108(6), 1488-1542.

Acemoglu, D., and Restrepo, P. (2019). Automation and new tasks: How technology displaces and reinstates labor. *Journal of Economic Perspectives*, 33(2), 3-30.

Acemoglu, D., and Restrepo, P. (2020). Robots and jobs: Evidence from US labor markets. *Journal of Political Economy*, 128(6).

Aghion P., B.F. Jones, C.I. Jones (2019). Artificial intelligence and economic growth. in *The Economics of Artificial Intelligence: An Agenda*, [eds. Agrawal, Gans, and Goldfarb], Chapter 9: 237-290

Agrawal A., J. Gans, and A. Goldfarb (Eds.)(2019). The economics of artificial intelligence: An agenda. Chicago: University of Chicago Press.

Amador, J., and Cabral., S. (2015). Global value chains, labour markets and productivity. In J. Amador and F. di Mauro (Eds.), *The age of global value chains, Maps and policy issues* (pp. 107–120). London: CEPR Press.

Antràs, P., and Chor, D. (2021). Global value chains. NBER Working Paper 28549. Cambridge

Autor, D. and Handel, M. (2013). Putting tasks to the test: Human capital, job tasks, and wages, *Journal of Labor Economics*, 31(2), 59–96.

Autor, D. H and Dorn, D. (2013). The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market, *American Economic Review*, 103(5): 1553–1597.

Autor, D. H., Dorn, D., and Hanson, G. H. (2015). Untangling trade and technology: Evidence from local labour markets. *The Economic Journal*, 125(584), 621-646.

Autor, D. H., Dorn, D., Hanson, G. H., and Song, J. (2014). Trade adjustment: Worker-level evidence. *The Quarterly Journal of Economics*, 129(4), 1799–1860.

Autor, D. H., Levy, F., and Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly Journal of Economics*, 118(4), 1279-1333.

Badri, A., Boudreau-Trudel, B., and Souissi, A. S. (2018). Occupational health and safety in the industry 4.0 era: A cause for major concern?. *Safety Science*, 109, 403-411.

Baldwin, R. (2012). Global supply chains: Why they emerged, why they matter, and where they are going . CEPR Discussion Papers. No. 9103

Baldwin, R. (2016). The Great Convergence. Information Technology and the New Globalization. Harvard University Press.

Baldwin, R., and Venables, A. J. (2013). Spiders and snakes: Offshoring and agglomeration in the global economy. *Journal of International Economics*, 90(2), 245-254.

Baruffaldi, S., et al. (2020). Identifying and measuring developments in artificial intelligence: Making the impossible possible, OECD Science, Technology and Industry Working Papers, No. 2020/05, OECD Publishing, Paris, <u>https://doi.org/10.1787/5f65ff7e-en</u>

Basco, S., and Mestieri, M. (2018). Mergers along the global supply chain: Information technologies and routine tasks. Oxford Bulletin of Economics and Statistics, 80(2), 406-433.

Baumgarten, D., Geishecker, I., Görg, H. (2013). Offshoring, tasks and the skill-wage pattern. *European Economic Review.*, 61, 132–152.

Berg-Beckhoff, G., Nielsen, G., Ladekjær Larsen, E. (2017). Use of information communication technology and stress, burnout, and mental health in older, middle-aged, and younger workers-results from a systematic review. *International Journal of Occupational and Environmental Health*, 23(2), 160-171.

Bisello, M., Fana, M., Fernández-Macías, E. and Torrejón Pérez, S. (2021) A comprehensive European database of tasks indices for socio-economic research, Labour Education and Technology JRC series 2021/04, European Commission, Seville.

Blinder, A. S. (2006). Offshoring: The Next Industrial Revolution. Foreign Aff., 85, 113.

Blinder, A. S. (2009). How many US jobs might be offshorable?. World Economics, 10(2), 41.

Blinder, A. S., and Krueger, A. B. (2013). Alternative measures of offshorability: a survey approach. *Journal of Labor Economics*, 31(S1), S97-S128.

Brynjolfsson, E., Mitchell, T. (2017). What can machine learning do? Workforce implications. *Science*, 358(6370), 1530-1534.

Brynjolfsson, E., Mitchell, T., Rock, D. (2018). What can machines learn, and what does it mean for occupations and the economy? *AEA Papers and Proceedings*. 108: 43-47.

Budría, S., and Milgram Baleix, J. (2020). Offshoring, job satisfaction and job insecurity. *Economics: The Open-Access, Open-Assessment E-Journal*, 14(2020-23), 1-32.

Calvino F., Criscuolo C., Marcolin L., Squicciarini M. (2018). A taxonomy of digital intensive sectors. OECD Science, Technology and Industry Working Papers 2018/14. <u>https://dx.doi.org/10.1787/f404736a-en</u>

Cardoso, M., Neves, P. C., Afonso, O., and Sochirca, E. (2021). The effects of offshoring on wages: a meta-analysis. *Review of World Economics*, 157(1), 149-179.

Clark, A. E. (2015). What makes a good job? Job quality and job satisfaction. *IZA World of Labor*. 215

Delautre G., Manrique E.E., Fenwick C. (2021) (Eds.) Decent work in a globalized economy: Lessons from public and private initiatives. International Labour Office – Geneva: ILO.

Ebenstein, A., Harrison, A., McMillan, M., and Phillips, S. (2014). Estimating the impact of trade and offshoring on American workers using the current population surveys. *Review of Economics and Statistics*, 96(4), 581–595

Egger, H., Kreickemeier, U., and Wrona, J. (2015). Offshoring domestic jobs. *Journal of International Economics*, 97(1), 112-125.

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

Feenstra, R. C., and Hanson, G. H. (1999). The Impact of Outsourcing and High-Technology Capital on Wages: Estimates For the United States, 1979-1990. *The Quarterly Journal of Economics*, 114(3), 907–940

Felten, E., M. Raj and R. Seamans (2019). The Occupational Impact of Artificial Intelligence on Labor: The Role of Complementary Skills and Technologies, NYU Stern School of Business, http://dx.doi.org/10.2139/ssrn.3368605.

Fleurbaey, M. (2015). Beyond income and wealth. Review of Income and Wealth, 61, 199-219

Franssen, L. (2019). Global value chains and relative labour demand: A geometric synthesis of neoclassical trade models. *Journal of Economic Surveys*, 33(4), 1232–1256.

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

Gallie, D., Felstead, A., and Green, F. (2012). Job preferences and the intrinsic quality of work: the changing attitudes of British employees 1992–2006. *Work, Employment and Society,* 26(5), 806–821.

Geishecker, I., and Görg, H. (2013). Services offshoring and wages: Evidence from micro data. *Oxford Economic Papers*, 65(1), 124–146.

Gimet, C., Guilhon, B., and Roux, N. (2015). Social upgrading in globalized production: The case of the textile and clothing industry. *International Labour Review*, 154(3), 303–327

Gisbert, J. R., Palau, C., Uriarte, M., Prieto, G., Palazón, J. A., Esteve, M., ... and González, A. (2014). Integrated system for control and monitoring industrial wireless networks for labor risk prevention. *Journal of Network and Computer Applications*, *39*, 233-252.

Goos, M. (2018). The impact of technological progress on labour markets: policy challenges. *Oxford Review of Economic Policy*, 34(3), 362-375.

Goos, M., Manning, A., and Salomons, A. (2014). Explaining job polarization: Routine-biased technological change and offshoring. *American Economic Review*, 104(8), 2509-26.

Graetz, G., and Michaels, G. (2018). Robots at work. *Review of Economics and Statistics*, 100(5), 753-768.

Gruetzemacher, R., Dorner, F. E., Bernaola-Alvarez, N., Giattino, C., & Manheim, D. (2021). Forecasting AI progress: A research agenda. *Technological Forecasting and Social Change*, 170, 120909.

Heckman, J. J., Lochner, L. J., and Todd, P. E. (2006). Earnings functions, rates of return and treatment effects: The Mincer equation and beyond. *Handbook of the Economics of Education*, *1*, 307-458.

Hummels, D., Munch, J. R., and Xiang, C. (2018). Offshoring and labor markets. *Journal of Economic Literature*, 56(3), 981–1028.

Lane, M., and Saint-Martin, A. (2021). The impact of Artificial Intelligence on the labour market: What do we know so far?. *OECD Social, Employment and Migration Working Papers* No. 256 <u>https://dx.doi.org/10.1787/7c895724-en</u>

Ledić, M., and Rubil, I. (2021). Beyond Wage Gap, Towards Job Quality Gap: The Role of Inter-Group Differences in Wages, Non-Wage Job Dimensions, and Preferences. *Social Indicators Research*, 1-39.

Lee, J., Gereffi, G., and Lee, S.-H. (2016). *Social Upgrading in Mobile Phone GVCs: Firm-level Comparisons of Working Conditions and Labour Rights.* in D. Nathan, M. Tewari, and S. Sarkar (Eds.), Labour in Global Value Chains in Asia (pp. 315–352). Cambridge: Cambridge University Press.

Lewandowski P., Park A., Hardy W., Du Y. (2019). Technology, Skills, and Globalization: Explaining International Differences in Routine and Nonroutine Work Using Survey Data. IZA Discussion Paper No.12339 http://ftp.iza.org/dp12339.pdf

Marcolin L., Miroudot S. and Squicciarini M. (2016). The routine content of occupations: new cross-country measures based on PIAAC, OECD Science, Technology and Industry Working Papers, 2016/02, OECD, Paris.

Milberg, W., and Winkler, D. (2011). Economic and social upgrading in global production networks: Problems of theory and measurement. *International Labour Review*, 150(3–4), 341–365.

Mira, M. C. (2021). New Model for Measuring Job Quality: Developing an European Intrinsic Job Quality Index (EIJQI). *Social Indicators Research*, 1-21.

Nadvi, K., Thoburn, J. T., Thang, B. T., Ha, N. T. T., Hoa, N. T., Le, D. H., and Armas, E. B. D. (2004). Vietnam in the global garment and textile value chain: impacts on firms and workers. *Journal of International Development*, *16*(1), 111-123

Nikulin D., Wolszczak-Derlacz J., Parteka A. (2021). Working conditions in Global Value Chains. Evidence for European employees. *Work, Employment and Society*. <u>https://doi.org/10.1177/0950017020986107</u>

OECD (2017). OECD Guidelines on Measuring the Quality of the Working Environment. Paris: Organisation for Economic Co-operation and Development.

OECD (2021). OECD AI Observatory, OECD, Paris, <u>https://www.oecd.ai/</u> [accessed on 01.09.2021]

Parteka, A., and Wolszczak-Derlacz, J. (2019). Global value chains and wages: Multi-country evidence from linked worker-industry data. *Open Economies Review*, 30(3), 505–539

Parteka, A., and Wolszczak-Derlacz, J. (2020). Wage response to global production links: evidence for workers from 28 European countries (2005–2014). *Review of World Economics*, 156, 769-801.

Rossi, A. (2013). Does Economic Upgrading Lead to Social Upgrading in Global Production Networks? Evidence from Morocco. *World Development*, 46, 223–233.

Salanova, M., Llorens, S., and Ventura, M. (2014). Technostress: The dark side of technologies. In *The impact of ICT on quality of working life* (pp. 87-103). Springer, Dordrecht.

Shen, L., and Silva, P. (2018). Value-added exports and US local labor markets: Does China really matter? *European Economic Review*, 101, 479–504.

Spitz-Oener, A. (2006). Technical change, job tasks, and rising educational demands: Looking outside the wage structure. *Journal of Labor Economics*, 24(2), 235-270.

Szymczak S., Parteka A, Wolszczak-Derlacz J. (2021). Position in global value chains and wages in Central and Eastern European countries, forthcoming in *European Journal of Industrial Relations*

Szymczak S., Wolszczak-Derlacz J. (2021). Global value chains and labour markets – simultaneous analysis of wages and employment, *Economic Systems Research*, forthcoming, <u>https://doi.org/10.1080/09535314.2021.1982678</u>

Tarafdar, M., Tu, Q., Ragu-Nathan, B. S., and Ragu-Nathan, T. S. (2007). The impact of technostress on role stress and productivity. *Journal of management information systems*, 24(1), 301-328.

Timmer, M. P., Dietzenbacher, E., Los, B., Stehrer, R. and de Vries, G. J. (2015). An Illustrated User Guide to the World Input–Output Database: the Case of Global Automotive Production, *Review of International Economics.*, 23: 575–605

Timmer, M., Los, B., Stehrer, R., and De Vries, G. (2016). An anatomy of the global trade slowdown based on the WIOD 2016 release (No. GD-162). Groningen Growth and Development Centre, University of Groningen.

UNIDO (2020). UNIDO's Industrial Development Report 2020. *Industrializing in the digital age*. United Nations Industrial Development Organization. <u>https://www.unido.org/resources-publications-flagship-publications-industrial-development-report-series/idr2020</u> [assessed on: 02 Sept, 2021]

Van Ark, B., A. Erumban, C. Corrado and G. Levanon (2016). Navigating the New Digital Economy: Driving Digital Growth and Productivity from Installation to Deployment, The Conference Board, New York.

Van Ark, B.; de Vries K., Erumban A. (2019). Productivity and Innovation Competencies in the Midst of the Digital Transformation Age. A EU-US Comparison. European Economy Discussion Paper 119.

Visser, J. (2019) 'ICTWSS Database. version 6.0.' Amsterdam: Amsterdam Institute for Advanced Labour Studies (AIAS), University of Amsterdam.

Wang, Z., Wei, S. J., and Zhu, K. (2013). *Quantifying international production sharing at the bilateral and sector levels* (No. w19677). National Bureau of Economic Research, revised February 2018

Webb, M. (2020), The Impact of Artificial Intelligence on the Labor Market. <u>https://www.michaelwebb.co/webb_ai.pdf</u> [assessed on 12 March, 2021]

WIPO (2019). WIPO Technology Trends 2019: Artificial Intelligence. Geneva: World Intellectual Property Organization. <u>https://www.wipo.int/edocs/pubdocs/en/wipo_pub_1055.pdf</u>

World Bank (2020). World Development Report 2020: Trading for development in the age of global value chains. Washington, DC: World Bank.

TABLES AND FIGURES



Figure 1. Non-wage aspects of working conditions in Europe – variation of job quality indices across <u>countries</u>

Note: High work intensity index should be interpreted as bad working conditions. The figures are computed using the sample of more than 9.5 millions of workers from 22 European countries with weights based on grossing-up factor for employees (from SES). The list of countries is provided in Table 1A, while job quality EWCS indices are described in detail in Table S2.

Source: own elaboration based on job quality indices from EWCS (2015) merged with SES (2014)



Figure 2. Non-wage aspects of working conditions in Europe – variation of job quality indices across <u>occupations</u>

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-Plan and machine operators, and assemblers, 9- Elementary workers. High work intensity index should be interpreted as bad working conditions. The figures are computed using the sample of more than 9.5 millions of workers from 22 European countries with weights based on grossing-up factor for employees(from SES).

Source: own elaboration based on job quality indices from EWCS (2015) merged with SES (2014)

Figure 3. Relationship between non-wage aspects of job quality and technological job content in Europe

A. social environment



B. skill and discretion



C. physical environment



[Figure 3 - cont.]

D. work intensity





Notes: Figures based on a sample of more than 9.5 millions of workers from 22 European countries. Dots correspond to country-industry weighted average across countries and sectors, with weights based on grossing-up factor for employees (from SES). To facilitate interpretation, we use the inverse of the original work intensity index.

Source: own elaboration based on job quality indices from EWCS (2015) merged with SES (2014) and technological exposure indicators (robot, software AI specific) from Webb (2020).



Figure 4. Relationship between non-wage aspects of job quality and intensity of GVC involvement in Europe

Note: Figures based on a sample of more than 9.5 million workers from 22 European countries. Dots correspond to country-industry weighted average across countries and sectors, with weights based on the grossing-up factor for employees (from SES). To facilitate interpretation, the inverse of the original work intensity index is used. GVC intensity measured in terms of sectoral share of foreign value added in gross exports.

Source: own elaboration based on job-quality indices from EWCS (2015) merged with SES (2014) and WIOD (2014)

	Working conditions (<i>WC</i>) capturing:						
	social environment (1)	skills and discretion (2)	physical environment (3)	work intensity (4)	prospects (5)	working time (6)	
GVC	-0.07 [0.046]	-0.182*** [0.052]	-0.119*** [0.046]	-0.173*** [0.045]	-0.155*** [0.048]	-0.156*** [0.044]	
$Tech_s^{MDIU}$	-0.325*** [0.026]	-0.209*** [0.028]	-0.230*** [0.026]	-0.240*** [0.027]	-0.298*** [0.027]	-0.319*** [0.026]	
$Tech_s^{DP}$	-0.018 [0.028]	0.199*** [0.031]	0.096*** [0.029]	0.027 [0.029]	0.043 [0.029]	0.004 [0.028]	
R2	0.79	0.75	0.79	0.78	0.78	0.8	
Ν	9214247	9218140	9218140	9216546	9218140	9218140	

Table 1. Estimation results - effects of sector digitalisation on working conditions

Notes: Estimations based on a sample of workers from 22 European countries. Personal, firm and sectoral variables included in all specifications –full results reporting all RHS variables in Table S3 in Supplementary materials. Industry technological classification (Van Ark et al., 2019 – Table 2A): MDIU - most digital intensive-using sectors, DP - Digital Producing, the default/missing: category: LDIU - Least digital intensive using. Country and sector fixed effects included. Normalized weighted regression with robust standard errors clustered at the firm level (in parentheses), the weights are based on the rescaled grossing-up factor for employees (from SES) normalized by the number of observations per country; *p \leq .10, **p \leq .05, ***p \leq .0.01 Source: own calculation based on data from EWCS, SES and WIOD.

	Working conditions (WC)capturing:					
	social environment	skills and discretion	physical environment	work intensity	prospects	working time
	(1)	(2)	(3)	(4)	(5)	(6)
GVC	-0.087	-0.211**	-0.232***	-0.098	-0.203***	-0.120*
	[0.073]	[0.086]	[0.071]	[0.068]	[0.077]	[0.070]
$Tech_s^{MDIU}$	-0.333***	-0.224***	-0.255***	-0.232***	-0.312***	-0.318***
	[0.028]	[0.030]	[0.028]	[0.029]	[0.029]	[0.028]
$Tech_s^{DP}$	0.02	0.266***	0.126***	0.071**	0.083***	0.048
	[0.031]	[0.033]	[0.031]	[0.032]	[0.032]	[0.031]
$Tech_s^{MDIU} \times GVC$	0.069	0.12	0.194***	-0.055	0.115	-0.001
	[0.077]	[0.089]	[0.074]	[0.073]	[0.078]	[0.073]
$Tech_s^{DP} \times GVC$	-0.253***	-0.444***	-0.172*	-0.315***	-0.260***	-0.306***
	[0.093]	[0.105]	[0.091]	[0.087]	[0.094]	[0.089]
R2	0.79	0.75	0.79	0.78	0.78	0.8
Ν	9214247	9218140	9218140	9216546	9218140	9218140

Table 2. Estimation results - effects of sector digitalization on working conditions, conditional upon GVC involvement (interaction term)

Notes: Estimations based on a sample of workers from 22 European countries. Personal, firm and sectoral control variables included – not reported (see full results in Table S3 in Supplementary materials). Sector digitalization class according to Van Ark et al., 2019 (Table 2A): LDIU - Least digital intensive using, MDIU - most digital intensive-using, DP - Digital Producing. The default category is: LDIU: Least digital intensive using sectors.



Figure 5. Predicted working conditions over GVC by sector digitalization level (illustrating the results from Table 2)

Notes: The lines on the chart correspond to sector digitalization class according to Van Ark et al., 2019 (Table 2A): LDIU - Least digital intensive using, MDIU - most digital intensive-using, DP - Digital Producing.

Source: own elaboration based on job-quality indices from EWCS (2015) merged with SES (2014), WIOD (2014) and technological exposure indicators as proposed by Webb (2020).

Working conditions (WC)capturing:						
	social environment (1)	skills and discretion (2)	physical environment (3)	work intensity (4)	prospects (5)	working time (6)
Panel A: sof	tware exposure					
GVC	-0.063	-0.167***	-0.105**	-0.166***	-0.146***	-0.148***
	[0.046]	[0.053]	[0.046]	[0.046]	[0.049]	[0.044]
Tech ^{software}	-0.002***	-0.004***	-0.004***	-0.002***	-0.002***	-0.002***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
R2	0.79	0.75	0.79	0.79	0.78	0.8
Ν	9214247	9218140	9218140	9216546	9218140	9218140
Panel B: rob	ot exposure					
GVC	-0.079*	-0.201***	-0.132***	-0.180***	-0.167***	-0.165***
	[0.045]	[0.047]	[0.043]	[0.045]	[0.046]	[0.042]
Tech _o ^{robot}	-0.007***	-0.014***	-0.009***	-0.005***	-0.009***	-0.006***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
R2	0.81	0.81	0.82	0.79	0.81	0.82
Ν	9214247	9218140	9218140	9216546	9218140	9218140
Panel C: AI	exposure					
GVC	-0.110**	-0.258***	-0.152***	-0.190***	-0.204***	-0.185***
	[0.046]	[0.050]	[0.045]	[0.045]	[0.047]	[0.043]
Tech _o ^{AI}	0.005***	0.010***	0.004***	0.002***	0.006***	0.004***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
\mathbb{R}^2	0.8	0.77	0.8	0.79	0.79	0.81
Ν	9214247	9218140	9218140	9216546	9218140	9218140

Table 3. Estimation results- effects of digital job content on working conditions

Note: Estimations based on a sample of workers from 22 European countries. Personal, firm and sectoral variables included in all specifications – detail results reported all RHS variable in Table S5 – S7 in Supplementary materials. Country and sector fixed effects included.

Table 4. Estimation results- effects of digital job content on working conditions,

	Working conditions (WC) capturing:					
	social environment (1)	skills and discretion (2)	physical environment (3)	work intensity (4)	prospects (5)	working time (6)
Panel A: software	exposure					
GVC	-0.168***	0.007	-0.019	-0.118**	-0.404***	-0.250***
	[0.058]	[0.067]	[0.055]	[0.060]	[0.059]	[0.052]
Tech _o ^{software}	-0.002***	-0.003***	-0.004***	-0.002***	-0.003***	-0.002***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
$Tech_o^{software} \times GVC$	0.002***	-0.004***	-0.002**	-0.001	0.006***	0.002***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
R2	0.79	0.75	0.79	0.79	0.78	0.8
Ν	9214247	9218140	9218140	9216546	9218140	9218140
Panel B: robot exp	osure					
GVC	-0.338***	-0.359***	-0.191***	-0.121**	-0.567***	-0.377***
	[0.049]	[0.053]	[0.048]	[0.053]	[0.050]	[0.046]
Tech _o ^{robot}	-0.008***	-0.015***	-0.010***	-0.005***	-0.010***	-0.007***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
$Tech_o^{robot} \times GVC$	0.006***	0.004***	0.001**	-0.001**	0.010***	0.005***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
R2	0.81	0.81	0.82	0.79	0.81	0.82
Ν	9214247	9218140	9218140	9216546	9218140	9218140
Panel C: AI exposi	ure					
GVC	-0.292***	-0.620***	-0.348***	-0.584***	-0.432***	-0.335***
	[0.056]	[0.065]	[0.054]	[0.060]	[0.058]	[0.052]
$Tech_o^{\mathcal{A}I}$	0.005***	0.009***	0.004***	0.001***	0.006***	0.003***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
$Tech_{o}^{AI} \times GVC$	0.004***	0.007***	0.004***	0.008***	0.004***	0.003***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
\mathbb{R}^2	0.8	0.77	0.8	0.79	0.79	0.81
Ν	9214247	9218140	9218140	9216546	9218140	9218140

Note: Estimations based on a sample of workers from 22 European countries. Personal and firms characteristics included as in Table S5. Country and sector fixed effects included.

Figure 6. Predicted working conditions at different levels of digital job content over GVC (illustrating the results from Table 4)



Panel 6.A. Software exposure









Note: The lines on each chart correspond to technological exposure intensity: occupations are divided into groups of low/medium/high degree of 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 (2014) and technological exposure indicators by Webb (2020).

APPENDIX

Table 1A. Set of countries

Country code	Country name	Country code	Country name
BE	Belgium	LU	Luxembourg
BG	Bulgaria	LV	Latvia
CY	Cyprus	MT	Malta
CZ	the Czech Republic	NL	the Netherlands
DE	Germany	NO	Norway
EE	Estonia	PL	Poland
ES	Spain	PT	Portugal
FR	France	RO	Romania
HU	Hungary	SE	Sweden
IT	Italy	SK	Slovakia
LT	Lithuania	UK	The United Kingdom

industry code (NACE rev.2)	digital industry taxonomy (Van Ark et al., 2019)	industry code (NACE rev.2)	digital industry taxonomy (Van Ark et al., 2019)
В	LDIU	D35	LDIU
C10-C12	LDIU	E36	LDIU
C10_C13	LDIU	E36_E37-E39	LDIU
C13-C15	LDIU	E37-E39	LDIU
C16_C17	MDIU	F	LDIU
C16_C17_C18	MDIU	G45_G46	MDIU
C18	MDIU	G47	MDIU
C19_C20_C21_C22	LDIU	H49_H50_H51_H52	LDIU
C19_C20_C21_C22_C23	LDIU	Н53	LDIU
C19_C20_C22	LDIU	Ι	LDIU
C19_C20_C22_C23	LDIU	J58_J59_J60	DP
C21	LDIU	J61_J62_J63	DP
C21_C26_C27_C33	DP	K64_K65_K66	MDIU
C21_C29_C30	MDIU	L68	LDIU
C23	LDIU	M69_M70	MDIU
C24_C25	LDIU	M69_M70_M71	MDIU
C24_C25_C28	LDIU	M71	MDIU
C26_C27_C33	DP	M72_M73_M74_M75	MDIU
C28	MDIU	M74_M75	MDIU
C29_C30	MDIU	N	MDIU
C29_C30_C31_C32	MDIU	O84	MDIU
C31_C32	MDIU	P85	LDIU
		Q	LDIU
		R_S	MDIU

Table 2A. List of industries and their technological (digital) classification

Note: DP= Digital Producing, LDIU = Least digital intensive using, MDIU = Most digital intensive-using sectors. In the case of grouped sectors we performed manual matching.

Table 3A. Correlations between non-wage job quality indices and wages (sample: 9.5

	wage	social environment	skills and discretion	physical environment	1/work intensity*	prospects	working time quality
wage	1						
social environment	-0,096	1					
skills and discretion	0,438	0,119	1				
physical environment	0,183	0,103	0,507	1			
1/work intensity*	-0,236	0,056	-0,225	0,218	1		
prospects	0,275	0,163	0,641	0,332	-0,228	1	
working time quality	-0,055	0,188	-0,090	0,146	0,220	-0,108	1

million workers from 22 European countries)

Note: *to facilitate interpretation, we use the inverse of original work intensity index. The calculations employ weights based on grossing-up factor for employees (from SES). The description of job quality indices is provided in Table S2 in Supplementary materials

Source: own elaboration based on indices from EWCS (2015) and wage data from SES (2014)

Table 4A. Summary	y statistics	of the	variables	used i	n the	estimation
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	N	Mean	Std. Dev.	Min	Max
Iob quality indices and working condition	ons				1
EWCS original job quality indices					
social environment	9522312	77.97	7.63	8.33	100.00
skills and discretion	9526356	57.29	14.73	8.32	96.48
physical environment	9526356	84.35	8.49	42.31	100.00
work intensity*	9524762	32.91	7.39	1.85	86.00
prospects	9526356	64.28	7.80	25.00	100.00
working time	9526356	71.55	5.51	30.33	87.90
Working conditions (in logs, as in eq. 1)	capturing:				1
social environment	9522224	2.20	0.89	-0.81	4.59
skills and discretion	9526268	1.87	1.05	-1.47	4.51
physical environment	9526268	2.28	0.92	-0.23	4.71
work intensity**	9524674	-5.61	0.86	-8.41	-2.28
prospects	9526268	2.01	0.94	-0.99	4.47
working time	9526268	2.12	0.90	-0.19	4.50
Technology exposure					
Software exposure	9526356	45.11	20.05	6.00	87.00
Robot exposure	9526356	44.83	23.78	10.00	86.00
AI exposure	9526356	47.67	19.93	11.00	90.00
Individual, job and firm characteristics		•	•		
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
FT	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
GVC measures					
FVA/Export	9502091	0.15	0.10	0.01	0.54
OFF	9526356	0.13	0.12	0.00	0.69
GII	9526356	0.28	0.20	0.00	0.99

Note: Weighted statistics, the weights are based on the rescaled grossing-up factor for employees (from SES) normalised by the number of observations per country. * Original EWCS job quality index: higher the working intensity implies lower job quality, ** Working conditions based on the inverse of work intensity job quality index. Source: own elaboration based on indices of job quality from EWCS (2015) merged with SES (2014) and technological exposure indicators from Webb (2020) and sectoral data from WIOD (2016).

SUPPLEMENTARY MATERIALS

to the paper:

Parteka A., Wolszczak-Derlacz J., Nikulin D. (2021) How digital technology affects working conditions in globally fragmented production chains: Evidence from Europe

This version: 05 November, 2021

Table S1. The	description	of data	sources
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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 the year 2015 (EWCS 2020 field work has been halted due to COVID). 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 working conditions (physical environment, work intensity, working time quality, social environment, skills and discretion, prospects); detailed description provided in Table S2

World 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 enables us to compute several measures of GVC intensity.	FVA/Export: Foreign value added in exports OFF: offshoring measure - value of imported intermediates to the industry's total output GII: global import intensity of production - intermediate imports along the chain final divided by the value of the final product; Prod: 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 Composite Index of Multi-level bargaining
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.	Export - share of merchandise exports in real GDP at current PPPs Import- Share of merchandise imports in real GDP at current PPPs

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 which 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 two 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

Table S2. Job quality indices according to EWCS

		 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)
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 last three years (or last 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)

	0	Dep.var: Working conditions (WC) capturing:				
	social environment	skills and discretion	physical environment	work intensity	prospects	working time
	(1)	(2)	(3)	(4)	(5)	(6)
ln_prod	0.103***	0.116***	0.112***	0.086***	0.110***	0.090***
	[0.008]	[0.009]	[0.008]	[0.007]	[0.008]	[0.008]
sex	0.133***	0.142***	0.104***	0.124***	0.140***	0.110***
	[0.002]	[0.003]	[0.002]	[0.003]	[0.002]	[0.002]
ageyoung	-0.138***	-0.133***	-0.141***	-0.158***	-0.128***	-0.134***
	[0.004]	[0.005]	[0.004]	[0.005]	[0.005]	[0.004]
ageaverage	-0.006***	0.003	-0.007***	-0.019***	0.001	-0.007***
	[0.002]	[0.003]	[0.002]	[0.002]	[0.002]	[0.002]
loweduc	-0.534***	-0.838***	-0.589***	-0.415***	-0.616***	-0.485***
	[0.004]	[0.005]	[0.004]	[0.004]	[0.004]	[0.003]
mededuc	-0.385***	-0.588***	-0.420***	-0.320***	-0.434***	-0.358***
	[0.004]	[0.006]	[0.004]	[0.004]	[0.004]	[0.004]
full time	0.068***	0.098***	0.059***	0.036***	0.074***	0.049***
-	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
shortdur	-0.318***	-0.391***	-0.317***	-0.287***	-0.340***	-0.305***
	[0.005]	[0.006]	[0.006]	[0.005]	[0.006]	[0.005]
meddur	-0.220***	-0.270***	-0.221***	-0.199***	-0.236***	-0.216***
	[0.005]	[0.007]	[0.006]	[0.005]	[0.006]	[0.005]
longdur	-0.125***	-0.159***	-0.126***	-0.111***	-0.134***	-0.122***
	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]
public	0.034***	0.048***	0.032***	0.043***	0.034***	0.039***
1	[0.008]	[0.009]	[0.007]	[0.007]	[0.008]	[0.007]
GVC	-0.07	-0.182***	-0.119***	-0.173***	-0.155***	-0.156***
	[0.046]	[0.052]	[0.046]	[0.045]	[0.048]	[0.044]
Tech ^{MDIU}	-0.325***	-0.209***	-0.230***	-0.240***	-0.298***	-0.319***
	[0.026]	[0.028]	[0.026]	[0.027]	[0.027]	[0.026]
Tech ^{DP}	-0.018	0.199***	0.096***	0.027	0.043	0.004
J	[0.028]	[0.031]	[0.029]	[0.029]	[0.029]	[0.028]
R ²	0.79	0.75	0.79	0.78	0.78	0.8
Ν	9214247	9218140	9218140	9216546	9218140	9218140

Table S3. Fu	ll estimation	results - effe	cts of sector	digitalisation	on working	conditions.
Technologic	al classificati	on of sectors :	according to	(Van Ark et al	., 2019)	

Note: Sex (male=1, 0- female). The 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 (more than 15 years of experience in enterprise), public enterprise. Technological classification of sectors (Van Ark et al., 2019): MDIU - most digital intensive-using sectors, DP - Digital Producing, the default: category: LDIU - Least digital intensive using. Country and sector fixed effects included. Normalized weighted regression with robust standard errors clustered at the firm level (in parentheses), the weights are based on the rescaled grossing-up factor for employees (from SES) normalised by the number of observations per country; $*p \le .10$, $**p \le .05$, $***p \le .0.01$ Source: own calculation based on data from EWCS, SES and WIOD

Table S4. Full estimation results - effects of sector digitalisation on working conditions, including interaction between *GVC* and *Techs*. Technological classification of sectors according to (Van Ark et al., 2019)

	Dep.var: Working conditions (WC) capturing:					
	social environment	skills and discretion	physical environment	work intensity	prospects	working time
	(1)	(2)	(3)	(4)	(5)	(6)
ln_prod	0.102***	0.115***	0.108***	0.088***	0.108***	0.091***
	[0.008]	[0.010]	[0.008]	[0.008]	[0.009]	[0.008]
sex	0.133***	0.142***	0.104***	0.124***	0.140***	0.110***
	[0.002]	[0.003]	[0.002]	[0.003]	[0.002]	[0.002]
ageyoung	-0.138***	-0.133***	-0.141***	-0.158***	-0.128***	-0.134***
	[0.004]	[0.005]	[0.004]	[0.005]	[0.005]	[0.004]
ageaverage	-0.006***	0.003	-0.007***	-0.019***	0.001	-0.007***
	[0.002]	[0.003]	[0.002]	[0.002]	[0.002]	[0.002]
loweduc	-0.534***	-0.838***	-0.589***	-0.415***	-0.616***	-0.485***
	[0.004]	[0.005]	[0.004]	[0.004]	[0.004]	[0.003]
mededuc	-0.385***	-0.588***	-0.420***	-0.320***	-0.434***	-0.358***
	[0.004]	[0.006]	[0.004]	[0.004]	[0.004]	[0.004]
full time	0.068***	0.098***	0.059***	0.036***	0.074***	0.049***
	[0.003]	[0.004]	[0.003]	[0.003]	[0.003]	[0.003]
shortdur	-0.318***	-0.391***	-0.317***	-0.286***	-0.340***	-0.305***
	[0.005]	[0.006]	[0.005]	[0.005]	[0.006]	[0.005]
meddur	-0.220***	-0.270***	-0.221***	-0.199***	-0.236***	-0.216***
	[0.005]	[0.007]	[0.006]	[0.005]	[0.006]	[0.005]
longdur	-0.125***	-0.158***	-0.126***	-0.111***	-0.134***	-0.122***
	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]
public	0.034***	0.049***	0.033***	0.044***	0.034***	0.039***
	[0.008]	[0.009]	[0.007]	[0.007]	[0.008]	[0.007]
GVC	-0.087	-0.211**	-0.232***	-0.098	-0.203***	-0.120*
	[0.073]	[0.086]	[0.071]	[0.068]	[0.077]	[0.070]
Tech_s^{MDIU}	-0.333***	-0.224***	-0.255***	-0.232***	-0.312***	-0.318***
	[0.028]	[0.030]	[0.028]	[0.029]	[0.029]	[0.028]
$Tech_s^{DP}$	0.02	0.266***	0.126***	0.071**	0.083***	0.048
	[0.031]	[0.033]	[0.031]	[0.032]	[0.032]	[0.031]
$Tech_s^{MDIU} \times GVC$	0.069	0.12	0.194***	-0.055	0.115	-0.001
	[0.077]	[0.089]	[0.074]	[0.073]	[0.078]	[0.073]
$Tech_s^{DP} \times GVC$	-0.253***	-0.444***	-0.172*	-0.315***	-0.260***	-0.306***
	[0.093]	[0.105]	[0.091]	[0.087]	[0.094]	[0.089]
\mathbb{R}^2	0.79	0.75	0.79	0.78	0.78	0.8
Ν	9214247	9218140	9218140	9216546	9218140	9218140

Notes: personal, firm and sectoral variables as in Table S3. The default category is: LDIU: Least digital intensive using. Other notes as under Table S3.

	Dep.var: Working conditions (<i>WC</i>) capturing:								
	social environment	skills and discretion	physical environment	work intensity	prospects	working time			
	(1)	(2)	(3)	(4)	(5)	(6)			
ln_prod	0.101***	0.112***	0.108***	0.084***	0.108***	0.088***			
	[0.008]	[0.009]	[0.008]	[0.007]	[0.008]	[0.008]			
sex	0.148***	0.174***	0.135***	0.141***	0.158***	0.126***			
	[0.002]	[0.003]	[0.002]	[0.003]	[0.002]	[0.002]			
ageyoung	-0.141***	-0.140***	-0.147***	-0.162***	-0.132***	-0.137***			
	[0.004]	[0.005]	[0.004]	[0.005]	[0.005]	[0.004]			
ageaverage	-0.007***	0.002	-0.008***	-0.020***	0.000	-0.008***			
	[0.002]	[0.003]	[0.002]	[0.002]	[0.002]	[0.002]			
loweduc	-0.518***	-0.803***	-0.556***	-0.397***	-0.596***	-0.467***			
	[0.004]	[0.006]	[0.004]	[0.004]	[0.004]	[0.003]			
mededuc	-0.375***	-0.566***	-0.399***	-0.308***	-0.421***	-0.346***			
	[0.004]	[0.006]	[0.004]	[0.004]	[0.005]	[0.004]			
full time	0.072***	0.106***	0.067***	0.041***	0.078***	0.054***			
0	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]			
shortdur	-0.316***	-0.388***	-0.314***	-0.285***	-0.338***	-0.304***			
	[0.005]	[0.006]	[0.006]	[0.005]	[0.006]	[0.005]			
meddur	-0.219***	-0.267***	-0.218***	-0.197***	-0.234***	-0.214***			
	[0.005]	[0.007]	[0.006]	[0.005]	[0.006]	[0.005]			
longdur	-0.124***	-0.156***	-0.124***	-0.110***	-0.133***	-0.121***			
0	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]			
public	0.034***	0.048***	0.032***	0.043***	0.033***	0.039***			
*	[0.008]	[0.009]	[0.008]	[0.007]	[0.008]	[0.007]			
GVC	-0.063	-0.167***	-0.105**	-0.166***	-0.146***	-0.148***			
	[0.046]	[0.053]	[0.046]	[0.046]	[0.049]	[0.044]			
Tech ^{software}	-0.002***	-0.004***	-0.004***	-0.002***	-0.002***	-0.002***			
v	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]			
\mathbb{R}^2	0.79	0.75	0.79	0.79	0.78	0.8			
Ν	9214247	9218140	9218140	9216546	9218140	9218140			

Table S5. Full estimation results - effects of <u>computerisation (software)</u> on working conditions

Note: sex (male=1, female=0). The 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 (more than 15 years of experience in enterprise), public enterprise. Country and sector fixed effects included. Normalized weighted regression with robust standard errors clustered at the firm level (in parentheses), the weights are based on the rescaled grossing-up factor for employees (from SES) normalised by the number of observations per country; *p \leq .10, **p \leq .0.01

	Dep.var: Working conditions (WC) capturing:						
	social environment	skills and discretion	physical environment	work intensity	prospects	working time	
	(1)	(2)	(3)	(4)	(5)	(6)	
ln_prod	0.093***	0.097***	0.099***	0.079***	0.098***	0.081***	
	[0.007]	[0.008]	[0.007]	[0.007]	[0.008]	[0.007]	
sex	0.171***	0.217***	0.154***	0.150***	0.187***	0.144***	
	[0.002]	[0.003]	[0.002]	[0.003]	[0.002]	[0.002]	
ageyoung	-0.147***	-0.151***	-0.152***	-0.164***	-0.139***	-0.142***	
	[0.004]	[0.004]	[0.004]	[0.005]	[0.004]	[0.004]	
ageaverage	-0.014***	-0.011***	-0.016***	-0.024***	-0.009***	-0.014***	
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	
loweduc	-0.329***	-0.431***	-0.320***	-0.273***	-0.359***	-0.301***	
	[0.004]	[0.005]	[0.003]	[0.004]	[0.004]	[0.003]	
mededuc	-0.250***	-0.319***	-0.242***	-0.226***	-0.264***	-0.236***	
	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	[0.003]	
full time	0.051***	0.063***	0.036***	0.024***	0.052***	0.034***	
0	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	
shortdur	-0.280***	-0.315***	-0.267***	-0.260***	-0.293***	-0.271***	
	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	
meddur	-0.193***	-0.217***	-0.186***	-0.180***	-0.202***	-0.191***	
	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	
longdur	-0.108***	-0.124***	-0.103***	-0.099***	-0.113***	-0.106***	
0	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	
public	0.032***	0.046***	0.031***	0.042***	0.032***	0.038***	
1	[0.008]	[0.008]	[0.007]	[0.007]	[0.008]	[0.007]	
GVC	-0.079*	-0.201***	-0.132***	-0.180***	-0.167***	-0.165***	
	[0.045]	[0.047]	[0.043]	[0.045]	[0.046]	[0.042]	
Tech robots	-0.007***	-0.014***	-0.009***	-0.005***	-0.009***	-0.006***	
v	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	
\mathbb{R}^2	0.81	0.81	0.82	0.79	0.81	0.82	
Ν	9214247	9218140	9218140	9216546	9218140	9218140	

Table S6. Full estimation results - effects of <u>robotisation</u> on working conditions

Notes: as under Table S5.

	Dep.var: Working conditions (WC) capturing:					
	social environment	skills and discretion	physical environment	work intensity	prospects	working time
	(1)	(2)	(3)	(4)	(5)	(6)
ln_prod	0.103***	0.117***	0.112***	0.086***	0.111***	0.090***
	[0.007]	[0.009]	[0.007]	[0.007]	[0.008]	[0.007]
SEX	0.093***	0.066***	0.071***	0.107***	0.090***	0.080***
	[0.002]	[0.003]	[0.002]	[0.003]	[0.002]	[0.002]
ageyoung	-0.130***	-0.118***	-0.134***	-0.155***	-0.118***	-0.128***
	[0.004]	[0.005]	[0.005]	[0.005]	[0.005]	[0.004]
ageaverage	-0.007***	0.002	-0.007***	-0.019***	-0.001	-0.008***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
loweduc	-0.477***	-0.732***	-0.543***	-0.392***	-0.546***	-0.444***
	[0.004]	[0.005]	[0.004]	[0.004]	[0.004]	[0.003]
mededuc	-0.344***	-0.512***	-0.387***	-0.303***	-0.385***	-0.328***
	[0.004]	[0.005]	[0.004]	[0.004]	[0.004]	[0.004]
full time	0.043***	0.050***	0.038***	0.026***	0.042***	0.031***
-	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
shortdur	-0.301***	-0.360***	-0.304***	-0.280***	-0.320***	-0.293***
	[0.005]	[0.006]	[0.005]	[0.005]	[0.005]	[0.005]
meddur	-0.211***	-0.253***	-0.214***	-0.195***	-0.224***	-0.209***
	[0.005]	[0.006]	[0.005]	[0.005]	[0.005]	[0.005]
longdur	-0.120***	-0.149***	-0.122***	-0.109***	-0.128***	-0.118***
	[0.004]	[0.005]	[0.005]	[0.004]	[0.005]	[0.004]
public	0.034***	0.048***	0.032***	0.043***	0.033***	0.039***
	[0.007]	[0.008]	[0.007]	[0.007]	[0.007]	[0.007]
GVC	-0.110**	-0.258***	-0.152***	-0.190***	-0.204***	-0.185***
	[0.046]	[0.050]	[0.045]	[0.045]	[0.047]	[0.043]
$Tech_o^{AI}$	0.005***	0.010***	0.004***	0.002***	0.006***	0.004***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
\mathbb{R}^2	0.8	0.77	0.8	0.79	0.79	0.81
Ν	9214247	9218140	9218140	9216546	9218140	9218140

Notes: as under Table S5.

	Dep.var: Working conditions (WC) capturing:							
	social environment	skills and discretion	physical environment	work intensity	prospects	working time		
	(1)	(2)	(3)	(4)	(5)	(6)		
ln_prod	0.103***	0.116***	0.112***	0.086***	0.110***	0.090***		
	[0.008]	[0.009]	[0.008]	[0.007]	[0.008]	[0.008]		
sex	0.133***	0.142***	0.104***	0.124***	0.140***	0.110***		
	[0.002]	[0.003]	[0.002]	[0.003]	[0.002]	[0.002]		
ageyoung	-0.138***	-0.133***	-0.141***	-0.158***	-0.128***	-0.134***		
	[0.004]	[0.005]	[0.004]	[0.005]	[0.005]	[0.004]		
ageaverage	-0.006***	0.003	-0.007***	-0.019***	0.001	-0.007***		
	[0.002]	[0.003]	[0.002]	[0.002]	[0.002]	[0.002]		
loweduc	-0.534***	-0.838***	-0.589***	-0.415***	-0.616***	-0.485***		
	[0.004]	[0.005]	[0.004]	[0.004]	[0.004]	[0.003]		
mededuc	-0.385***	-0.588***	-0.420***	-0.320***	-0.434***	-0.358***		
	[0.004]	[0.006]	[0.004]	[0.004]	[0.004]	[0.004]		
full time	0.068***	0.098***	0.059***	0.036***	0.074***	0.049***		
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]		
shortdur	-0.318***	-0.391***	-0.317***	-0.287***	-0.340***	-0.305***		
	[0.005]	[0.006]	[0.006]	[0.005]	[0.006]	[0.005]		
meddur	-0.220***	-0.270***	-0.221***	-0.199***	-0.236***	-0.216***		
	[0.005]	[0.007]	[0.006]	[0.005]	[0.006]	[0.005]		
longdur	-0.125***	-0.159***	-0.126***	-0.111***	-0.134***	-0.122***		
	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]		
public	0.034***	0.048***	0.032***	0.043***	0.034***	0.039***		
	[0.008]	[0.009]	[0.007]	[0.007]	[0.008]	[0.007]		
GVC	-0.07	-0.182***	-0.119***	-0.173***	-0.155***	-0.156***		
	[0.046]	[0.052]	[0.046]	[0.045]	[0.048]	[0.044]		
$Tech_s^{MIIU}$	-0.325***	-0.209***	-0.230***	-0.240***	-0.298***	-0.319***		
	[0.026]	[0.028]	[0.026]	[0.027]	[0.027]	[0.026]		
$Tech_s^{IP}$	-0.018	0.199***	0.096***	0.027	0.043	0.004		
	[0.028]	[0.031]	[0.029]	[0.029]	[0.029]	[0.028]		
\mathbb{R}^2	0.79	0.75	0.79	0.78	0.78	0.8		
Ν	9214247	9218140	9218140	9216546	9218140	9218140		

Table S8. Full estimation results - effects of sector digitalisation_on working conditions. Robustness check: Alternative technological classification of sectors (Van Ark et al., 2016)

Notes: personal, firm and sectoral variables as in Table S3. Industry technological classification (Van Ark et al., 2016): MIIU - Most ICT intensive using, IP – ICT producing, the default: category: LIIU- Least ICT intensive using. Country and sector fixed effects included. Normalized weighted regression with robust standard errors clustered at the firm level (in parentheses), the weights are based on the rescaled grossing-up factor for employees (from SES) normalised by the number of observations per country; $*p \le .10$, $**p \le .05$, $***p \le .0.01$

Table S9. Full estimation results - effects of sector digitalisation on working conditions, including interaction between GVC and $Tech_s$. Robustness check: Alternative technological classification of sectors (Van Ark et al., 2016)

0		Dep.var: W	orking condition	s (WC) capt	uring:	
	social	skills and	physical	work	prospects	working
	environment	discretion	environment	intensity	prospects	time
	(1)	(2)	(3)	(4)	(5)	(6)
ln_prod	0.103***	0.115***	0.108***	0.086***	0.109***	0.089^{***}
	[0.008]	[0.010]	[0.008]	[0.008]	[0.009]	[0.008]
sex	0.133***	0.142***	0.104***	0.124***	0.140***	0.110***
	[0.002]	[0.003]	[0.002]	[0.003]	[0.002]	[0.002]
agevoung	-0.138***	-0.133***	-0.141***	-	-0.128***	-0.134***
82 8	[0.004]	[0.005]	[0 004]	0.158***	[0 005]	[0.004]
	0.004	0.003	0.007***	[0.005]	0.001	0.007***
ageaverage	-0.000***	0.005	-0.007	- 0.019***	0.001	-0.007***
	[0.002]	[0.003]	[0.002]	[0.002]	[0.002]	[0.002]
landus	-0.534***	-0.838***	-0.589***	-	-0.616***	-0.484***
loweauc				0.415***		
	[0.004]	[0.005]	[0.004]	[0.004]	[0.004]	[0.003]
mededuc	-0.385***	-0.588***	-0.420***	- 0.2 2 0***	-0.434***	-0.358***
	[0 004]	[0 006]	[0 004]	0. <i>32</i> 0 ⁴⁰⁴⁴	[0 004]	[0 004]
full times	0.068***	0.098***	0.059***	0.036***	0.074***	0.049***
juu ume	[0 003]	[0 004]	[0 003]	[0.003]	[0.003]	[0 003]
	-0.317***	-0 391***	-0 317***	[0.005]	-0 340***	_0.305***
shortdur	-0.517	-0.371	-0.517	0.286***	-0.5+0	-0.505
	[0.005]	[0.006]	[0.005]	[0.005]	[0.006]	[0.005]
moddur	-0.220***	-0.270***	-0.221***	-	-0.236***	-0.216***
тешин	FO. 00 F 1	F0.00 7	50.00.41	0.199***	F0 00 41	F0.00 F 1
	[0.005]	[0.007]	[0.006]	[0.005]	[0.006]	[0.005]
longdur	-0.125***	-0.158***	-0.126***	- 0.111***	-0.134***	-0.122***
	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]
tublic	0.034***	0.049***	0.033***	0.043***	0.034***	0.039***
pnou	[0.008]	[0.009]	[0.007]	[0.007]	[0.008]	[0.007]
CVC	-0.077	-0.249**	-0.291***	-0.158**	-0.223**	-0.194**
070	[0.085]	[0.098]	[0.081]	[0.075]	[0.091]	[0.081]
	-0 331***	-0 227***	-0.260***	-	-0 313***	-0 329***
Tech _s ^{MIIU}	0.551	0.227	0.200	0.242***	0.515	0.327
	[0.029]	[0.031]	[0.029]	[0.029]	[0.030]	[0.029]
Tech _s ^{IP}	0.021	0.262***	0.120***	0.064**	0.081**	0.04
	[0.031]	[0.033]	[0.031]	[0.032]	[0.032]	[0.031]
$Tech_s^{MIIU} \times GVC$	0.051	0.155	0.249***	0.021	0.13	0.088
	[0.088]	[0.100]	[0.085]	[0.081]	[0.092]	[0.084]
$T_{ach}^{IP} \times C V C$	-0.262**	-0.407***	-0.114	-	-0.240**	-0.235**
		50 4 4 45	50,0000	0.257***	TO 40 7	F0.0007
	[0.102]	[0.114]	[0.099]	[0.094]	[0.106]	[0.098]
\mathbb{R}^2	0.79	0.75	0.79	0.78	0.78	0.8
Ν	9214247	9218140	9218140	9216546	9218140	9218140

Notes: as under Table S8. The default category is: LIIU- Least ICT intensive using

Figure S1 (illustrating the results from Table S9). Predicted working conditions at different levels of sector digitalisation. Robustness check: Alternative technological classification of sectors (Van Ark et al., 2016)



Notes: The lines on the chart correspond to sector digitalization. Technological classification of sectors according to Van Ark et al. (2016): LIIU- Least ICT intensive using, MIIU - Most ICT intensive using, IP- ICT producing Source: own elaboration based on job-quality indices from EWCS (2015) merged with SES (2014), WIOD (2014) and technological exposure indicators by Webb (2020).

				`		,
		W	orking conditions (W	VC) capturing:		
	social	skills and	physical	work	a vo ca o ato	working
	environment	discretion	environment	intensity	prospects	time
GVC	-0.07	-0.182***	-0.119***	-0.173***	-0.155***	-0.156***
	[0.046]	[0.052]	[0.046]	[0.045]	[0.048]	[0.044]
Tech _s ^{MDIU}	-0.325***	-0.209***	-0.230***	-0.240***	-0.298***	-0.319***
	[0.026]	[0.028]	[0.026]	[0.027]	[0.027]	[0.026]
$Tech_s^{DP}$	-0.018	0.199***	0.096***	0.027	0.043	0.004
	[0.028]	[0.031]	[0.029]	[0.029]	[0.029]	[0.028]
Coord	0.170***	0.174***	0.185***	0.204***	0.175***	0.180***
	[0.007]	[0.008]	[0.007]	[0.006]	[0.007]	[0.006]
R2	0.79	0.75	0.79	0.78	0.78	0.8
Ν	9214247	9218140	9218140	9216546	9218140	9218140

Table S10. Estimation results - effects of sector digitalisation on working conditions, Robustness check: the role of labour market institutions (additional variable *Coord*)

Notes: Personal, firms and sectoral characteristics included as in Table S3. Country and sector fixed effects included. *Coord* stands for coordination of wage-setting: 1 - centralised or industry-level bargaining, 0 - mixed industry and firm-level bargaining

Source: own calculation based on data from EWCS, SES and WIOD

Table S11. Estimation results	- effects of sector digitalisation on working conditions,
including interaction between	GVC and Tech. Robustness check: the role of labour
market institutions (additional	variable Coord)

		Wo	rking conditions (W	WC) capturing:		
	social environment	skills and discretion	physical environment	work intensity	prospects	working time
GVC	-0.087	-0.211**	-0.232***	-0.098	-0.203***	-0.120*
	[0.073]	[0.086]	[0.071]	[0.068]	[0.077]	[0.070]
Tech _s ^{MDIU}	-0.333***	-0.224***	-0.255***	-0.232***	-0.312***	-0.318***
	[0.028]	[0.030]	[0.028]	[0.029]	[0.029]	[0.028]
$Tech_s^{DP}$	0.02	0.266***	0.126***	0.071**	0.083***	0.048
	[0.031]	[0.033]	[0.031]	[0.032]	[0.032]	[0.031]
$Tech_s^{MDIU} \times GVC$	0.069	0.12	0.194***	-0.055	0.115	-0.001
	[0.077]	[0.089]	[0.074]	[0.073]	[0.078]	[0.073]
$Tech_s^{DP} \times GVC$	-0.253***	-0.444***	-0.172*	-0.315***	-0.260***	-0.306***
	[0.093]	[0.105]	[0.091]	[0.087]	[0.094]	[0.089]
Coord	0.170***	0.174***	0.188***	0.200***	0.176***	0.177***
	[0.007]	[0.009]	[0.007]	[0.007]	[0.008]	[0.007]
R2	0.79	0.75	0.79	0.78	0.78	0.8
N	9214247	9218140	9218140	9216546	9218140	9218140

Notes: Personal, firms and sectoral characteristics included as in Table S3. Country and sector fixed effects included. *Coord* stands for coordination of wage-setting: 1 - centralised or industry-level bargaining, 0 - mixed industry and firm-level bargaining

		Dep.var:	Working conditions	s (WC) capturing	:	
	social	skills and	physical	work	prospects	working
D 14	environment	discretion	environment	intensity	Prospecto	time
Panel A: so	oftware exposure	2				
GVC	-0.063	-0.167***	-0.105**	-0.166***	-0.146***	-0.148***
	[0.046]	[0.053]	[0.046]	[0.046]	[0.049]	[0.044]
Tech _o software	-0.002***	-0.004***	-0.004***	-0.002***	-0.002***	-0.002***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Coord	2.061***	0.207***	0.159***	0.147***	0.168***	0.145***
	[0.020]	[0.007]	[0.006]	[0.006]	[0.006]	[0.006]
R2	0.79	0.75	0.79	0.79	0.78	0.8
Ν	9214247	9218140	9218140	9216546	9218140	9218140
Panel B: ro	obot exposure					
GVC	-0.079*	-0.201***	-0.132***	-0.180***	-0.167***	-0.165***
	[0.045]	[0.047]	[0.043]	[0.045]	[0.046]	[0.042]
Tech _o robot	-0.007***	-0.014***	-0.009***	-0.005***	-0.009***	-0.006***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Coord	2.065***	0.245***	0.188***	0.163***	0.191***	0.163***
	[0.020]	[0.006]	[0.006]	[0.006]	[0.006]	[0.005]
R2	0.81	0.81	0.82	0.79	0.81	0.82
Ν	9214247	9218140	9218140	9216546	9218140	9218140
Panel C: A	I exposure					
GVC	-0.110**	-0.258***	-0.152***	-0.190***	-0.204***	-0.185***
	[0.046]	[0.050]	[0.045]	[0.045]	[0.047]	[0.043]
Tech _o ^{AI}	0.005***	0.010***	0.004***	0.002***	0.006***	0.004***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Coord	2.077***	0.291***	0.203***	0.170***	0.221***	0.179***
	[0.020]	[0.007]	[0.006]	[0.006]	[0.006]	[0.006]
R2	0.8	0.77	0.8	0.79	0.79	0.81
Ν	9214247	9218140	9218140	9216546	9218140	9218140

Table S12. Estimation results: effects of digital job content on working conditions, Robustness check: the role of labour market institutions (additional variable *Coord*)

Notes: Personal, firms and sectoral characteristics included as in Table S5. Country and sector fixed effects included. *Coord* stands for coordination of wage-setting: 1 - centralised or industry-level bargaining, 0 - mixed industry and firm-level bargaining

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		Dep.var: Work	king conditions (W	C) capturing:		
	social environment	skills and discretion	physical environment	work intensity	prospects	working time
Panel A: software	exposure			·		
GVC	-0.168***	0.007	-0.019	-0.118**	-0.404***	-0.250***
	[0.058]	[0.067]	[0.055]	[0.060]	[0.059]	[0.052]
Tech _o software	-0.002***	-0.003***	-0.004***	-0.002***	-0.003***	-0.002***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Tech _o software×GVC	0.002***	-0.004***	-0.002**	-0.001	0.006***	0.002***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Coord	0.165***	0.169***	0.178***	0.201***	0.166***	0.174***
	[0.007]	[0.008]	[0.007]	[0.007]	[0.007]	[0.006]
R2	0.79	0.75	0.79	0.79	0.78	0.8
N	9214247	9218140	9218140	9216546	9218140	9218140
Panel B: robot exp	osure					
GVC	-0.338***	-0.359***	-0.191***	-0.121**	-0.567***	-0.377***
	[0.049]	[0.053]	[0.048]	[0.053]	[0.050]	[0.046]
Tech _o robot	-0.008***	-0.015***	-0.010***	-0.005***	-0.010***	-0.007***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
$Tech_{o}^{robot} \times GVC$	0.006***	0.004***	0.001**	-0.001**	0.010***	0.005***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Coord	0.169***	0.184***	0.193***	0.212***	0.171***	0.180***
	[0.006]	[0.007]	[0.006]	[0.007]	[0.007]	[0.006]
R2	0.81	0.81	0.82	0.79	0.81	0.82
Ν	9214247	9218140	9218140	9216546	9218140	9218140
Panel C: AI expos	ure					
GVC	-0.292***	-0.620***	-0.348***	-0.584***	-0.432***	-0.335***
	[0.056]	[0.065]	[0.054]	[0.060]	[0.058]	[0.052]
Tech _o ^{AI}	0.005***	0.009***	0.004***	0.001***	0.006***	0.003***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
$Tech_{o}^{AI} \times GVC$	0.004***	0.007***	0.004***	0.008***	0.004***	0.003***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Coord	0.196***	0.222***	0.205***	0.215***	0.206***	0.198***
	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]	[0.006]
R2	0.8	0.77	0.8	0.79	0.79	0.81
N	9214247	9218140	9218140	9216546	9218140	9218140

Table S13. Estimation results: effects of digital job content on working conditions, including interaction between GVC and Tech₀. Robustness check: the role of labour market institutions (additional variable *Coord*)

Notes: Personal, firms and sectoral characteristics included as in Table S5. Country and sector fixed effects included. *Coord* stands for coordination of wage-setting: 1 - centralised or industry-level bargaining, 0 - mixed industry and firm-level bargaining

Table S14. Estimation results - effects of sector digitalisation on working conditions, Robustness check: the role of labour market institutions (additional variable Level: *Composite Index of Multi-level bargaining*)

		Wor	king conditions (W	C) capturing:		
	social environment	skills and discretion	physical environment	work intensity	prospects	working time
GVC	-0.07	-0.182***	-0.119***	-0.173***	-0.155***	-0.156***
	[0.046]	[0.052]	[0.046]	[0.045]	[0.048]	[0.044]
Tech _s ^{MDIU}	-0.325***	-0.209***	-0.230***	-0.240***	-0.298***	-0.319***
	[0.026]	[0.028]	[0.026]	[0.027]	[0.027]	[0.026]
$Tech_s^{DP}$	-0.018	0.199***	0.096***	0.027	0.043	0.004
	[0.028]	[0.031]	[0.029]	[0.029]	[0.029]	[0.028]
Level	0.047***	0.048***	0.051***	0.056***	0.048***	0.050***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
R2	0.79	0.75	0.79	0.78	0.78	0.8
N	9214247	9218140	9218140	9216546	9218140	9218140

Notes: Personal, firms and sectoral characteristics included as in Table S3. Country and sector fixed effects included. *Level* -composite index of multi-level bargaining.

Table S15. Estimation results - effects of sector digitalisation on working conditions, including interaction between GVC and Techs, Robustness check: the role of labour market institutions (additional variable Level: Composite Index of Multi-level bargaining)

		W	orking condition (V	WC) capturing:		
	social environment	skills and discretion	physical environment	work intensity	prospects	working time
GVC	-0.087	-0.211**	-0.232***	-0.098	-0.203***	-0.120*
	[0.073]	[0.086]	[0.071]	[0.068]	[0.077]	[0.070]
$Tech_s^{MDIU}$	-0.333***	-0.224***	-0.255***	-0.232***	-0.312***	-0.318***
	[0.028]	[0.030]	[0.028]	[0.029]	[0.029]	[0.028]
$Tech_s^{DP}$	0.02	0.266***	0.126***	0.071**	0.083***	0.048
	[0.031]	[0.033]	[0.031]	[0.032]	[0.032]	[0.031]
$Tech_s^{MDIU} \times GVC$	0.069	0.12	0.194***	-0.055	0.115	-0.001
	[0.077]	[0.089]	[0.074]	[0.073]	[0.078]	[0.073]
$Tech_s^{DP} \times GVC$	-0.253***	-0.444***	-0.172*	-0.315***	-0.260***	-0.306***
	[0.093]	[0.105]	[0.091]	[0.087]	[0.094]	[0.089]
Level	0.047***	0.048***	0.052***	0.055***	0.049***	0.049***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
R2	0.79	0.75	0.79	0.78	0.78	0.8
N	9214247	9218140	9218140	9216546	9218140	9218140

Notes: Personal, firms and sectoral characteristics included as in Table S3. Country and sector fixed effects included. *Level* -composite index of multi-level bargaining.

		Dep.var:	Working condition	s (WC) capturing	5	
	social environment	skills and discretion	physical environment	work intensity	prospects	working time
Panel A: s	oftware exposu	e		÷		
GVC	-0.063	-0.167***	-0.105**	-0.166***	-0.146***	-0.148***
	[0.046]	[0.053]	[0.046]	[0.046]	[0.049]	[0.044]
Tech _o ^{software}	-0.002***	-0.004***	-0.004***	-0.002***	-0.002***	-0.002***
÷	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Level	0.046***	0.046***	0.049***	0.055***	0.047***	0.048***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
R2	0.79	0.75	0.79	0.79	0.78	0.8
Ν	9214247	9218140	9218140	9216546	9218140	9218140
Panel B: ro	obot exposure					
GVC	-0.079*	-0.201***	-0.132***	-0.180***	-0.167***	-0.165***
	[0.045]	[0.047]	[0.043]	[0.045]	[0.046]	[0.042]
Tech _o ^{robot}	-0.007***	-0.014***	-0.009***	-0.005***	-0.009***	-0.006***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Level	0.049***	0.052***	0.054***	0.058***	0.051***	0.051***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
R2	0.81	0.81	0.82	0.79	0.81	0.82
Ν	9214247	9218140	9218140	9216546	9218140	9218140
Panel C: A	I exposure					
GVC	-0.110**	-0.258***	-0.152***	-0.190***	-0.204***	-0.185***
	[0.046]	[0.050]	[0.045]	[0.045]	[0.047]	[0.043]
Tech _o ^{AI}	0.005***	0.010***	0.004***	0.002***	0.006***	0.004***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Level	0.054***	0.061***	0.057***	0.059***	0.057***	0.055***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
R2	0.8	0.77	0.8	0.79	0.79	0.81
Ν	9214247	9218140	9218140	9216546	9218140	9218140

Table S16. Estimation results: effects of digital job content on working conditions. Robustness check: the role of labour market institutions (additional variable Level: *Composite Index of Multi-level bargaining*)

Notes: Personal, firms and sectoral characteristics included as in Table S5. Country and sector fixed effects included. *Level* -composite index of multi-level bargaining.

Table S17. Estimation results: effects of digital job content on working conditions, including interaction between *GVC* and *Tech*₀, Robustness check: the role of labour market institutions (additional variable: Composite Index of Multi-level bargaining)

		Dep.var: W	orking conditions (W	C) capturing:		
	social	skills and	physical	work	prospects	working
Danal A: coftwar	environment	discretion	environment	intensity	1 1	time
Fallel A. softwar	e exposure		0.040	0.440484		
GVC	-0.168***	0.007	-0.019	-0.118**	-0.404***	-0.250***
	[0.058]	[0.067]	[0.055]	[0.060]	[0.059]	[0.052]
Tech _o ^{softwar}	-0.002***	-0.003***	-0.004***	-0.002***	-0.003***	-0.002***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
$Tech_o^{softwar} \times GVC$	0.002***	-0.004***	-0.002**	-0.001	0.006***	0.002***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Level	0.045***	0.047***	0.049***	0.055***	0.046***	0.048***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
R2	0.79	0.75	0.79	0.79	0.78	0.8
Ν	9214247	9218140	9218140	9216546	9218140	9218140
Panel B: robot e:	xposure					
GVC	-0.338***	-0.359***	-0.191***	-0.121**	-0.567***	-0.377***
	[0.049]	[0.053]	[0.048]	[0.053]	[0.050]	[0.046]
Tech _o ^{robot}	-0.008***	-0.015***	-0.010***	-0.005***	-0.010***	-0.007***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Tech _o ^{robot} ×GVC	0.006***	0.004***	0.001**	-0.001**	0.010***	0.005***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Level	0.047***	0.051***	0.053***	0.058***	0.047***	0.050***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
R2	0.81	0.81	0.82	0.79	0.81	0.82
Ν	9214247	9218140	9218140	9216546	9218140	9218140
Panel C: AI expo	osure					
GVC	-0.292***	-0.620***	-0.348***	-0.584***	-0.432***	-0.335***
	[0.056]	[0.065]	[0.054]	[0.060]	[0.058]	[0.052]
Tech _e ^{AI}	0.005***	0.009***	0.004***	0.001***	0.006***	0.003***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
$Tech_{o}^{AI} \times GVC$	0.004***	0.007***	0.004***	0.008***	0.004***	0.003***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Level	0.054***	0.061***	0.057***	0.059***	0.057***	0.055***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
R2	0.8	0.77	0.8	0.79	0.79	0.81
Ν	9214247	9218140	9218140	9216546	9218140	9218140

Notes: Personal, firms and sectoral characteristics included as in Table S5. Country and sector fixed effects included. *Level* -composite index of multi-level bargaining.

`		W	Vorking condition (WC) capturing	:	
	social environment	skills and discretion	physical environment	work intensity	prospects	working time
GVC	-0.087	-0.211**	-0.232***	-0.098	-0.203***	-0.120*
	[0.073]	[0.086]	[0.071]	[0.068]	[0.077]	[0.070]
Tech _s ^{MDIU}	-0.333***	-0.224***	-0.255***	-0.232***	-0.312***	-0.318***
	[0.028]	[0.030]	[0.028]	[0.029]	[0.029]	[0.028]
$Tech_s^{DP}$	0.02	0.266***	0.126***	0.071**	0.083***	0.048
	[0.031]	[0.033]	[0.031]	[0.032]	[0.032]	[0.031]
$Tech_s^{MDIU} \times GVC$	0.069	0.12	0.194***	-0.055	0.115	-0.001
	[0.077]	[0.089]	[0.074]	[0.073]	[0.078]	[0.073]
$Tech_s^{DP} \times GVC$	-0.253***	-0.444***	-0.172*	-0.315***	-0.260***	-0.306***
	[0.093]	[0.105]	[0.091]	[0.087]	[0.094]	[0.089]
Export	0.158***	0.161***	0.175***	0.186***	0.163***	0.165***
*	[0.007]	[0.008]	[0.007]	[0.007]	[0.007]	[0.007]
R2	0.79	0.75	0.79	0.78	0.78	0.8
N	9214247	9218140	9218140	9216546	9218140	9218140

Table S18. Estimation results - effects of sector digitalisation on working conditions, including interaction between *GVC* and *Techs*. Robustness check: countries' trade openness (additional variable: export share of GDP)

Notes: Personal, firms and sectoral characteristics included as in Table S3. Country and sector fixed effects included. Source: own calculation based on data from EWCS, SES and WIOD

_		Working condition (WC) capturing:						
	social environment	skills and discretion	physical environment	work intensity	prospects	working time		
GVC	-0.087	-0.211**	-0.232***	-0.098	-0.203***	-0.120*		
	[0.073]	[0.086]	[0.071]	[0.068]	[0.077]	[0.070]		
Tech ^{MDIU}	-0.333***	-0.224***	-0.255***	-0.232***	-0.312***	-0.318***		
·	[0.028]	[0.030]	[0.028]	[0.029]	[0.029]	[0.028]		
Tech _s ^{DP}	0.02	0.266***	0.126***	0.071**	0.083***	0.048		
	[0.031]	[0.033]	[0.031]	[0.032]	[0.032]	[0.031]		
$Tech_s^{MDIU} \times GVC$	0.069	0.12	0.194***	-0.055	0.115	-0.001		
	[0.077]	[0.089]	[0.074]	[0.073]	[0.078]	[0.073]		
$Tech_s^{DP} \times GVC$	-0.253***	-0.444***	-0.172*	-0.315***	-0.260***	-0.306***		
	[0.093]	[0.105]	[0.091]	[0.087]	[0.094]	[0.089]		
Import	0.156***	0.160***	0.173***	0.184***	0.162***	0.163***		
*	[0.007]	[0.008]	[0.007]	[0.006]	[0.007]	[0.006]		
R2	0.79	0.75	0.79	0.78	0.78	0.8		
Ν	9214247	9218140	9218140	9216546	9218140	9218140		

Table S19. Estimation results - effects of sector digitalisation on working conditions, including interaction between *GVC* and *Techs*, Robustness check: countries' trade openness (additional variable: import share of GDP)

Notes: Personal, firms and sectoral characteristics included as in Table S3. Country and sector fixed effects included. Source: own calculation based on data from EWCS, SES and WIOD

		Dep.var: W	orking conditions (V	WC) capturing:		
	social environment	skills and discretion	physical environment	work intensity	prospects	working time
Panel A: software	e exposure			<u>,</u>		
GVC	-0.168***	0.007	-0.019	-0.118**	-0.404***	-0.250***
	[0.058]	[0.067]	[0.055]	[0.060]	[0.059]	[0.052]
Tech ^{software}	-0.002***	-0.003***	-0.004***	-0.002***	-0.003***	-0.002***
*	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Tech ^{software} ×GVC	0.002***	-0.004***	-0.002**	-0.001	0.006***	0.002***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Export	0.153***	0.157***	0.166***	0.187***	0.154***	0.162***
	[0.006]	[0.007]	[0.006]	[0.006]	[0.007]	[0.006]
32	0.79	0.75	0.79	0.79	0.78	0.8
V	9214247	9218140	9218140	9216546	9218140	9218140
Panel B: robot ex	xposure					
GVC	-0.338***	-0.359***	-0.191***	-0.121**	-0.567***	-0.377***
	[0.049]	[0.053]	[0.048]	[0.053]	[0.050]	[0.046]
Tech or robot	-0.008***	-0.015***	-0.010***	-0.005***	-0.010***	-0.007***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
$Tech_o^{robot} \times GVC$	0.006***	0.004***	0.001**	-0.001**	0.010***	0.005***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Export	0.157***	0.171***	0.179***	0.196***	0.159***	0.167***
	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]
R2	0.81	0.81	0.82	0.79	0.81	0.82
N	9214247	9218140	9218140	9216546	9218140	9218140
Panel C: AI expo	osure					
GVC	-0.292***	-0.620***	-0.348***	-0.584***	-0.432***	-0.335***
	[0.056]	[0.065]	[0.054]	[0.060]	[0.058]	[0.052]
Fech _o ^{AI}	0.005***	0.009***	0.004***	0.001***	0.006***	0.003***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
$\operatorname{Tech}^{AI}_{o} \times \operatorname{GVC}$	0.004***	0.007***	0.004***	0.008***	0.004***	0.003***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Export	0.181***	0.206***	0.190***	0.200***	0.191***	0.184***
-	[0.006]	[0.007]	[0.006]	[0.006]	[0.006]	[0.006]
R2	0.8	0.77	0.8	0.79	0.79	0.81
V	9214247	9218140	9218140	9216546	9218140	9218140

Table S20. Estimation results: effects of digital job content on working conditions, including interaction between GVC and $Tech_0$, Robustness check: countries' trade openness (additional variable: export share of GDP)

Personal, firms and sectoral characteristics included as in Table S5. Country and sector fixed effects included. Source: own calculation based on data from EWCS, SES and WIOD

		Dep.var: Wo	rking conditions (V	WC) capturing		
	social environment	skills and discretion	physical environment	work intensity	prospects	working time
Panel A: software	e exposure			2		
GVC	-0.168***	0.007	-0.019	-0.118**	-0.404***	-0.250***
	[0.058]	[0.067]	[0.055]	[0.060]	[0.059]	[0.052]
Tech ^{software}	-0.002***	-0.003***	-0.004***	-0.002***	-0.003***	-0.002***
0	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Tech_software×GVC	0.002***	-0.004***	-0.002**	-0.001	0.006***	0.002***
0	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Import	0.151***	0.155***	0.164***	0.185***	0.153***	0.160***
1	[0.006]	[0.007]	[0.006]	[0.006]	[0.006]	[0.006]
R2	0.79	0.75	0.79	0.79	0.78	0.8
Ν	9214247	9218140	9218140	9216546	9218140	9218140
Panel B: robot ex	xposure					
GVC	-0.338***	-0.359***	-0.191***	-0.121**	-0.567***	-0.377***
	[0.049]	[0.053]	[0.048]	[0.053]	[0.050]	[0.046]
Tech ^{robot}	-0.008***	-0.015***	-0.010***	-0.005***	-0.010***	-0.007***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
$Tech_{o}^{robot} \times GVC$	0.006***	0.004***	0.001**	-0.001**	0.010***	0.005***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Import	0.155***	0.169***	0.177***	0.194***	0.157***	0.165***
1	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]
R <i>2</i>	0.81	0.81	0.82	0.79	0.81	0.82
Ν	9214247	9218140	9218140	9216546	9218140	9218140
Panel C: AI expo	osure					
GVC	-0.292***	-0.620***	-0.348***	-0.584***	-0.432***	-0.335***
	[0.056]	[0.065]	[0.054]	[0.060]	[0.058]	[0.052]
Tech _o ^{AI}	0.005***	0.009***	0.004***	0.001***	0.006***	0.003***
÷	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
$Tech_{o}^{AI} \times GVC$	0.004***	0.007***	0.004***	0.008***	0.004***	0.003***
-	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Import	0.180***	0.204***	0.189***	0.198***	0.189***	0.182***
-	[0.006]	[0.007]	[0.006]	[0.006]	[0.006]	[0.006]
R2	0.8	0.77	0.8	0.79	0.79	0.81
Ν	9214247	9218140	9218140	9216546	9218140	9218140

Table S21. Estimation results: effects of digital job content on working conditions, including interaction between GVC and Tech_o, Robustness check: countries' trade openness (additional variable: import share of GDP)

Personal, firms and sectoral characteristics included as in Table S5. Country and sector fixed effects included. Source: own calculation based on data from EWCS, SES and WIOD

	Working conditions (WC) capturing:									
	social environment	skills and discretion	physical environment	work intensity	prospects	working time				
	(1)	(2)	(3)	(4)	(5)	(6)				
OFF	-0.013	-0.187***	-0.072*	-0.103**	-0.089**	-0.077*				
	[0.045]	[0.050]	[0.043]	[0.044]	[0.045]	[0.041]				
Tech ^{MDIU}	-0.325***	-0.220***	-0.234***	-0.245***	-0.302***	-0.323***				
	[0.027]	[0.028]	[0.027]	[0.027]	[0.027]	[0.027]				
Tech _s ^{DP}	-0.02	0.189***	0.091***	0.019	0.036	-0.003				
	[0.029]	[0.031]	[0.029]	[0.029]	[0.029]	[0.028]				
R2	0.79	0.75	0.79	0.78	0.78	0.8				
Ν	9235678	9239722	9239722	9238128	9239722	9239722				

Table S22. Estimation results - effects of sector digitalisation on working conditions. Robustness check: *GVC* substituted by offshoring index (*OFF*)

Notes: Personal, firms and sectoral characteristics included as in Table S3. Country and sector fixed effects included. *OFF* – ratio of imported intermediates to sectoral output (Feenstra and Hanson, 1999) Source: own calculation based on data from EWCS, SES and WIOD

Table S23. Estimation results - effects of sector digitalisation on working conditions, including interaction between *Tech*^s and *GVC*; Robustness check: *GVC* substituted by offshoring index (OFF)

	Working conditions (WC) capturing:							
	social	skills and	physical	work	prospects	working		
	environment	discretion	environment	intensity		time		
	(1)	(2)	(3)	(4)	(5)	(6)		
OFF	0.05	-0.125*	-0.037	0.034	-0.031	0.015		
	[0.065]	[0.075]	[0.063]	[0.061]	[0.066]	[0.062]		
Tech _s ^{MDIU}	-0.316***	-0.214***	-0.231***	-0.220***	-0.295***	-0.307***		
	[0.028]	[0.030]	[0.028]	[0.029]	[0.029]	[0.028]		
Tech _s ^{DP}	0.017	0.242***	0.124***	0.066**	0.075**	0.037		
	[0.031]	[0.032]	[0.031]	[0.031]	[0.031]	[0.031]		
$Tech_s^{MDIU} \times OFF$	-0.049	-0.013	0	-0.176***	-0.036	-0.100*		
	[0.062]	[0.073]	[0.061]	[0.057]	[0.061]	[0.059]		
$Tech_s^{DP} \times OFF$	-0.289***	-0.420***	-0.261***	-0.361***	-0.308***	-0.309***		
	[0.080]	[0.092]	[0.079]	[0.075]	[0.080]	[0.077]		
R2	0.79	0.75	0.79	0.78	0.78	0.8		
Ν	9235678	9239722	9239722	9238128	9239722	9239722		

Notes: Personal, firms and sectoral characteristics included as in Table S3. Country and sector fixed effects included. *OFF* – ratio of imported intermediates to sectoral output (Feenstra and Hanson, 1999) Sources: own calculation based on data from EW/CS. SES and WIOD.

	Dep.var: Working conditions (WC) capturing								
	social environment	skills and discretion	physical environment	work intensity	prospects	working time			
Panel A: s	oftware exposure	2							
OFF	-0.01	-0.180***	-0.065	-0.099**	-0.085*	-0.073*			
	[0.045]	[0.050]	[0.043]	[0.044]	[0.046]	[0.042]			
Tech ^{software}	-0.002***	-0.004***	-0.004***	-0.002***	-0.002***	-0.002***			
Ū.	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]			
R2	0.79	0.75	0.79	0.79	0.78	0.8			
Ν	9235678	9239722	9239722	9238128	9239722	9239722			
Panel B: re	obot exposure								
OFF	-0.003	-0.167***	-0.058	-0.096**	-0.076*	-0.067*			
	[0.044]	[0.045]	[0.041]	[0.044]	[0.044]	[0.040]			
Tech _o ^{robot}	-0.007***	-0.014***	-0.009***	-0.005***	-0.009***	-0.006***			
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]			
R2	0.81	0.81	0.82	0.79	0.81	0.82			
Ν	9235678	9239722	9239722	9238128	9239722	9239722			
Panel C: A	I exposure								
OFF	-0.025	-0.209***	-0.082*	-0.108**	-0.104**	-0.085**			
	[0.045]	[0.048]	[0.043]	[0.044]	[0.044]	[0.041]			
Tech _o ^{AI}	0.005***	0.010***	0.004***	0.002***	0.006***	0.004***			
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]			
R2	0.8	0.77	0.8	0.79	0.79	0.8			
Ν	9235678	9239722	9239722	9238128	9239722	9239722			

Table S24. Estimation results: effects of digital job content on working conditions, *Robustness check: GVC substituted by offshoring index (OFF)*

Notes: Personal, firms and sectoral characteristics included as in Table S5. Country and sector fixed effects included. *OFF* – ratio of imported intermediates to sectoral output (Feenstra and Hanson, 1999) Source: own calculation based on data from EWCS, SES and WIOD

U		Dep.var: W	orking conditions (N	WC) capturing				
	social environment	skills and discretion	physical environment	work intensity	prospects	working time		
Panel A: software exposure								
OFF	-0.023	0.077	0.078	-0.007	-0.247***	-0.122**		
	[0.058]	[0.063]	[0.052]	[0.061]	[0.057]	[0.050]		
Tech software	-0.002***	-0.003***	-0.003***	-0.002***	-0.003***	-0.002***		
0	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]		
Tech _o ^{software} ×OFF	0.000	-0.005***	-0.003***	-0.002**	0.003***	0.001		
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]		
R2	0.79	0.75	0.79	0.79	0.78	0.8		
Ν	9235678	9239722	9239722	9238128	9239722	9239722		
		F	Panel B: robot expos	ure				
OFF	-0.231***	-0.313***	-0.119**	-0.04	-0.479***	-0.289***		
	[0.051]	[0.054]	[0.047]	[0.054]	[0.051]	[0.046]		
Tech ^{robot}	-0.008***	-0.014***	-0.009***	-0.005***	-0.010***	-0.007***		
U	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]		
Tech _o ^{robot} ×OFF	0.004***	0.003***	0.001***	-0.001*	0.008***	0.004***		
	[0.000]	[0.000]	[0.000]	[0.001]	[0.000]	[0.000]		
R2	0.81	0.81	0.82	0.79	0.81	0.82		
Ν	9235678	9239722	9239722	9238128	9239722	9239722		
			Panel C: AI exposu	re				
OFF	-0.151***	-0.515***	-0.217***	-0.442***	-0.230***	-0.171***		
	[0.054]	[0.060]	[0.050]	[0.057]	[0.053]	[0.047]		
Tech_AI	0.005***	0.009***	0.004***	0.001***	0.006***	0.004***		
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]		
$Tech_{o}^{AI} \times OFF$	0.002***	0.006***	0.003***	0.006***	0.002***	0.002***		
~	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]		
R ²	0.8	0.77	0.8	0.79	0.79	0.8		
Ν	9235678	9239722	9239722	9238128	9239722	9239722		

Table S25. Estimation results: effects of digital job content on working conditions, including interaction between GVC and Tech, Robustness check: GVC substituted by offshoring index (OFF)

Notes: Personal, firms and sectoral characteristics included as in Table S5. Country and sector fixed effects included. *OFF* – ratio of imported intermediates to sectoral output (Feenstra and Hanson, 1999)

	Working condition (WC) capturing:									
	social environment (1)	skills and discretion (2)	physical environment (3)	work intensity (4)	prospects (5)	working time (6)				
GII	-0.027	-0.125***	-0.056*	-0.117***	-0.071**	-0.074**				
	[0.031]	[0.034]	[0.030]	[0.031]	[0.032]	[0.029]				
Tech _s ^{MDIU}	-0.327***	-0.222***	-0.235***	-0.252***	-0.304***	-0.326***				
	[0.027]	[0.028]	[0.027]	[0.027]	[0.028]	[0.027]				
Tech _s ^{DP}	-0.022	0.187***	0.090***	0.015	0.034	-0.005				
	[0.029]	[0.031]	[0.029]	[0.029]	[0.029]	[0.029]				
R2	0.79	0.75	0.79	0.78	0.78	0.8				
Ν	9235678	9239722	9239722	9238128	9239722	9239722				

Table S26. Estimation results - effects of sector digitalisation on working conditions, Robustness check: GVC measured by GII

Notes: Personal, firms and sectoral characteristics included as in Table S3. Country and sector fixed effects included. *GII* – global import intensity of production (Timmer et al., 2016).

Source: own calculation based on data from EWCS, SES and WIOD

Table S27. Estimation results - effects of sector digitalisation on working conditions, including interaction between *Tech*^s and *GVC*. Robustness check: *GVC* measured by *GII*

	Working condition (WC) capturing:								
	social environment	skills and discretion	physical environment	work intensity	prospects	working time			
	(1)	(2)	(3)	(4)	(5)	(6)			
GII	-0.035	-0.155***	-0.103**	-0.078*	-0.101**	-0.065			
	[0.050]	[0.055]	[0.047]	[0.046]	[0.050]	[0.047]			
Tech _s ^{MDIU}	-0.335***	-0.243***	-0.260***	-0.240***	-0.322***	-0.327***			
	[0.031]	[0.033]	[0.030]	[0.031]	[0.031]	[0.030]			
$Tech_s^{DP}$	0.009	0.239***	0.111***	0.059*	0.063*	0.029			
	[0.033]	[0.035]	[0.033]	[0.033]	[0.034]	[0.033]			
$Tech_s^{MDIU} \times GII$	0.037	0.087	0.094**	-0.033	0.071	0.009			
	[0.048]	[0.054]	[0.046]	[0.044]	[0.047]	[0.045]			
$Tech_s^{DP} \times GII$	-0.126**	-0.213***	-0.093*	-0.168***	-0.121**	-0.134**			
	[0.059]	[0.064]	[0.056]	[0.053]	[0.058]	[0.056]			
R2	0.79	0.75	0.79	0.78	0.78	0.8			
Ν	9235678	9239722	9239722	9238128	9239722	9239722			

Notes: Personal, firms and sectoral characteristics included as in Table S3. Country and sector fixed effects included. *GII* – global import intensity of production (Timmer et al., 2016).

Dep.var: Working conditions (WC) capturing								
	social environment	skills and discretion	physical environment	work intensity	prospects	working time		
Panel A: software exposure								
GII	-0.023	-0.117***	-0.048	-0.113***	-0.066**	-0.070**		
	[0.031]	[0.034]	[0.030]	[0.031]	[0.032]	[0.029]		
Tech _o software	-0.002***	-0.004***	-0.004***	-0.002***	-0.002***	-0.002***		
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]		
R2	0.79	0.75	0.79	0.79	0.78	0.8		
Ν	9235678	9239722	9239722	9238128	9239722	9239722		
Panel B: ro	obot exposure							
GII	-0.024	-0.119***	-0.051*	-0.114***	-0.067**	-0.071**		
	[0.031]	[0.031]	[0.029]	[0.030]	[0.031]	[0.029]		
Tech _o ^{robot}	-0.007***	-0.014***	-0.009***	-0.005***	-0.009***	-0.006***		
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]		
R2	0.81	0.81	0.82	0.79	0.81	0.82		
Ν	9235678	9239722	9239722	9238128	9239722	9239722		
Panel C: A	I exposure							
GII	-0.042	-0.154***	-0.068**	-0.123***	-0.090***	-0.085***		
	[0.031]	[0.033]	[0.030]	[0.031]	[0.031]	[0.029]		
Tech _o ^{AI}	0.005***	0.010***	0.004***	0.002***	0.006***	0.004***		
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]		
R2	0.8	0.77	0.8	0.79	0.79	0.8		
Ν	9235678	9239722	9239722	9238128	9239722	9239722		

Table S28. Estimation results: effects of digital job content on working conditions. Robustness check: GVC measured by GII

Notes: Personal, firms and sectoral characteristics included as in Table S5. Country and sector fixed effects included. *GII* – global import intensity of production (Timmer et al., 2016)

Table S29. Estimation results: effects of digital job content on working conditions, including interaction between GVC and Tech. Robustness check: GVC measured by GII

Dep.var: Working conditions (WC) capturing								
	social environment	skills and discretion	physical environment	work intensity	prospects	working time		
Panel A: software exposure								
GII	-0.055	0.046	0.028	-0.052	-0.189***	-0.097***		
	[0.037]	[0.040]	[0.034]	[0.039]	[0.036]	[0.033]		
Tech _o ^{software}	-0.002***	-0.003***	-0.003***	-0.002***	-0.003***	-0.002***		
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]		
$Tech_o^{software} \times GII$	0.001	-0.003***	-0.002***	-0.001**	0.002***	0.001		
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]		
R2	0.79	0.75	0.79	0.79	0.78	0.8		
Ν	9235678	9239722	9239722	9238128	9239722	9239722		
Panel B: robot exposure								
GII	-0.174***	-0.210***	-0.087***	-0.056	-0.314***	-0.191***		
	[0.033]	[0.034]	[0.030]	[0.035]	[0.032]	[0.030]		
Tech _o ^{robot}	-0.008***	-0.015***	-0.010***	-0.005***	-0.010***	-0.007***		
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]		
$Tech_o^{robot} \times GII$	0.003***	0.002***	0.001**	-0.001***	0.005***	0.002***		
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]		
R2	0.81	0.81	0.82	0.79	0.81	0.82		
Ν	9235678	9239722	9239722	9238128	9239722	9239722		
Panel C: AI expos	sure							
GII	-0.167***	-0.399***	-0.205***	-0.386***	-0.239***	-0.182***		
	[0.037]	[0.040]	[0.034]	[0.039]	[0.037]	[0.033]		
$Tech_o^{\mathcal{A}I}$	0.005***	0.008***	0.004***	0.001***	0.006***	0.003***		
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]		
$Tech_o^{AI} \times GII$	0.002***	0.005***	0.003***	0.005***	0.003***	0.002***		
	[0.000]	[0.001]	[0.000]	[0.000]	[0.000]	[0.000]		
R2	0.8	0.77	0.8	0.79	0.79	0.81		
Ν	9235678	9239722	9239722	9238128	9239722	9239722		

Notes: Personal, firms and sectoral characteristics included as in Table S5. Country and sector fixed effects included. *GII* – global import intensity of production (Timmer et al., 2016)

Original citation:

Parteka A., Wolszczak-Derlacz J., Nikulin D. (2021). How digital technology affects working conditions in globally fragmented production chains: evidence from Europe. GUT FME Working Papers Series A, No 4/2021(66). Gdansk (Poland): Gdansk University of Technology, Faculty of Management and Economics.

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