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The joint impact of global value chains and technological exposure on job quality and wages in Europe

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Abstract. *We use a micro-level dataset for workers from 22 European countries to assess whether technological exposure affects the relationship between global value chains (GVCs) and working conditions, quantified by several aspects of job quality and wages. We compare the effects across types of technological exposure, differentiating between software and robots versus artificial intelligence technology. In general, involvement in GVCs correlates negatively with wages and (slightly) positively with some non-monetary aspects of job quality. We show that exposure to digital technology does not alter this core relationship in an economically meaningful way.*

Keywords: *working conditions, wage, global value chains, GVC, technological exposure, digital technology, Europe.*

1. Introduction

This article assesses the relationship between the working conditions of European employees and two major global trends: production fragmentation across borders as reflected in involvement in global value chains (GVCs); and technological progress driven by digital technologies that combine hardware (advanced robots and 3D printers), software (big data analytics, cloud computing and artificial intelligence (AI)) and connectivity (UNIDO 2019, xvi). In particular, the main goal of this article is to investigate whether digitally driven technological factors alter the core relationship between GVCs and different aspects of working conditions (wages and job quality) in developed countries.

There are many determinants of working conditions, including the growth of temporary employment (Aleksynska 2018), characteristics of employment structure within firms (Clark, D'Ambrosio and Zhu 2021), organization of work and the social relations embedded in the labour process (Briken et al. 2017; Gandini 2019; Harley 2018), the use (and abuse) of technologies (Salanova, Llorens and Ventura 2014; Badri, Boudreau-Trudel and Souissi 2018; Brynjolfsson, Mitchell and Rock 2018;) and the complexity of value chains (Berliner et al. 2015; Bernhardt and Pollak 2016; Parteka, Wolszczak-Derlacz and Nikulin 2024). In this article, we focus on the interplay between the latter two forces: technological progress and GVCs. The proliferation of GVCs raises concerns about their impact on working conditions (e.g. Barrientos, Gereffi and Rossi 2011; Barrientos et al. 2016; Berliner et al. 2015; Bernhardt and Pollak 2016; Nikulin, Wolszczak-Derlacz and Parteka 2022), the protection of workers' rights (Delautre, Echeverría Manrique and Fenwick 2021) and social relations at work (Reinecke et al. 2018). Some 70 per cent of global trade involves GVCs,[1] such that changes in business models due to cross-border production fragmentation cannot be neglected. At the same time, GVCs cannot be isolated from the exponential progress in digital technologies, including AI, which has been another powerful force in recent decades (Aghion, Jones and Jones 2019; Hernandez and Brown 2020; Lu and Zhou 2021). It has fuelled the intensification of cross-border production links and the "second unbundling" (Baldwin 2013) of, and interacting with, modern labour markets (Agrawal, Gans and Goldfarb 2019; Acemoglu and Restrepo 2018; Brynjolfsson and Mitchell 2017; Brynjolfsson, Mitchell and Rock 2018; Lane and Saint-Martin 2021; OECD 2023).

We focus on developed economies in Europe because the struggle to ensure conditions of decent work, addressed in international policy measures and strategies such as the United Nations 2030 Sustainable Development Goals, is not restricted to the developing world and problems such as hazardous conditions or child labour (Delautre, Echeverría Manrique and Fenwick 2021). The quality of working life is not only diversified across European industries and jobs (Eurofound 2020), depending on the sex, age, contractual status and occupation of workers (Eurofound 2021) but is also – at least in some respects – globally unsatisfactory. This problem is reflected in the European Union's current 2030 Agenda, which "calls for opportunities for full employment and *decent work* for all" (Goal 8 – our own emphasis).[2] It was also previously reflected in the Treaty on the Functioning of the European Union, the Lisbon Strategy and the Europe 2020 Strategy, which all established improving labour rights as one of the main targets for European labour markets. Still, the 2021 European Working Conditions Telephone Survey (EWCS) (Eurofound 2022) reports that 49 per cent of European workers frequently work at high speed, while 19 per cent said that their job involved being in emotionally disturbing situations. Moreover, "the reality of the changing workplace" results in the growth of psychosocial risk or work intensity and the blurred boundaries between work and non-work life (Eurofound 2021). These problems could be exacerbated by the fact that in many European countries, employment shares have increased in occupations with greater exposure to modern digital technologies, including AI (Albanesi et al. 2023).

A reading of the related literature (see section 2) allows us to identify several specific research gaps to be addressed in our Europe-focused study. First, GVC-focused research has

[1] See https://www.oecd.org/en/topics/global-value-and-supply-chains.html (accessed 16 April 2025).
[2] See https://ec.europa.eu/eurostat/web/sdi/database/decent-work-and-economic-growth (accessed 16 April 2025).

rarely dealt with such aspects of work as occupational safety and health, job satisfaction or job security (Budría and Baleix 2020; Geishecker 2012). Even when the social consequences of GVCs are analysed, they are mainly quantified in terms of their impact on wages or the risk of job displacement (Baumgarten, Geishecker and Görg 2013; Ebenstein et al. 2014; Geishecker, Görg and Munch 2010; Parteka and Wolszczak-Derlacz 2019 and 2020; Shen and Silva 2018; Hummels, Munch and Xiang 2018). These studies do not capture the full complexity of working conditions, including less quantifiable aspects such as the quality of physical working environments, social support and management quality, career development prospects, work–life balance and the impact of work intensity on health and well-being (Eurofound 2021). We investigate the multifaceted nature of working conditions, including the economic dimension of work and its effects on living conditions, by providing estimates using monetary information (wage data) and information on different aspects of job quality.[3] Our key underlying assumption is that non-wage job dimensions affect employees in ways that are as important as wages in terms of well-being. Such an approach is in line with the concept of equivalent income used in the well-being literature (e.g. see Decancq, Fleurbaey and Schokkaert 2015; Fleurbaey 2015) or demand-control theory (Karasek and Theorell 1990), linking job demands and job strain with the mental and physical condition of workers. One may postulate that poor working conditions – not including wages – are compensated by higher salaries, but the empirical evidence for this is rather weak (e.g. see Bonhomme and Jolivet 2009; Fernández and Nordman 2009).

Second, studies focusing on job quality have thus far not assessed the role of production fragmentation in the context of the dynamically changing technological landscape. Social scientists seem to be several steps behind the actual advancements in the digital sphere, including the increasing role of AI technologies in the work context (Albanesi et al. 2023; OECD 2023). Digital technologies, including AI, can be quantified at the level of occupations using the task-based approach (Autor, Levy and Murnane 2003; Acemoglu and Restrepo 2018) that views occupations as a bundle of tasks differing in exposure to technology. We can now measure the AI exposure of tasks typical for a given occupation (Webb 2020) and of the abilities that those tasks require (Felten, Raj and Seamans 2018 and 2019) or the "suitability for machine learning" of specific work activities, tasks and occupations (Brynjolfsson, Mitchell and Rock 2018). Such measures have mainly been used to assess the impact of AI on employment patterns in the United States (Acemoglu et al. 2022) or in Europe (Albanesi et al. 2023). While there is rich evidence about the effects of information and communications technology or automation on workers performing routine tasks (e.g. Autor, Levy and Murnane 2003; Autor and Handel 2013; Autor and Dorn 2013; Frey and Osborne 2017; Goos, Manning and Salomons 2014; Marcolin, Miroudot and Squicciarini 2016; Spitz-Oener 2006; Acemoglu and Restrepo 2020), the first studies on worker-level exposure to AI have only just started to emerge. In the light of a study for the European Parliament (Deshpande et al. 2021), the current evidence and forecasts for the link between AI and labour markets are rather mixed. In terms of the impact on working standards, the study indicates that AI offers opportunities (reducing dangerous or unhealthy working conditions and improving accessibility to certain jobs) but also creates physical and psychosocial risks.

[3] We apply ILO and EWCS definitions. The ILO defines a "job" as "a set of tasks and duties performed, or meant to be performed, by one person, including for an employer or in self employment". "Occupation" is defined as a "set of jobs whose main tasks and duties are characterized by a high degree of similarity" (https://isco-ilo.netlify.app/en/isco-08/). "Job quality", according to the EWCS, includes "job features captured from an objective perspective, which can be observed and are related to meeting people's needs from work. It is made up of all the characteristics of work and employment that have been proven to have a causal relationship with health and well-being. Positive and negative features of the jobs are included. These indicators reflect the job resources (physical, psychological, social or organisational aspects) and job demands, or the processes that influence them" (https://www.eurofound.europa.eu/en/topic/job-quality). "Working conditions" is an even broader concept: it refers to "the conditions in and under which work is performed [… including] the economic dimension of work and effects on living conditions" (https://www.eurofound.europa.eu/en/topic/working-conditions) (links accessed 12 May 2025).

We contribute to the literature on working conditions and GVCs by analysing the role played by developments in AI alongside other features of technological progress (computerization and automation). Our econometric results show that, on average, involvement in GVCs correlates negatively with wages and (slightly) positively with some non-monetary aspects of job quality, especially once we consider the exposure of jobs to software or robots. As regards the exposure of jobs to AI, the effect of the intensification of GVC involvement is negative for wages but insignificant for job quality. We thus find that the influence of GVCs on wages and various facets of job quality may be diversified, such that non-wage aspects should be analysed in addition to the wages themselves. At the same time, we show that the role of digital technology in affecting the GVC–working conditions nexus is marginal or even insignificant. In other words, technological factors do not affect the core relationship between working conditions and GVCs in an economically meaningful way.

Following our review of literature related to the determinants of working conditions in section 2, section 3 documents some descriptive evidence on working conditions in Europe. In section 4, we present our key results, linking observed trends in job quality and wages with GVCs and the technological features of jobs. We discuss our conclusions in section 5.

2. Determinants of working conditions: A literature review

The literature on working conditions is extensive. As there is no unique definition of working conditions and/or job quality (Clark 2015; Steffgen, Sischka and Fernandez de Henestrosa 2020), multidimensional workers' well-being may be analysed from different perspectives, implicating alternative methodological approaches. We can quantify the economic aspects of jobs using monetary indicators (such as wages), combined with information on working time or type of work (evening/night/shift/temporary) (e.g. Aleksynska 2018; Piasna 2018; Rossi 2013). However, other non-monetary features, reflected in such intrinsic aspects of work as autonomy, social utility, interpersonal relations or social context of work, constitute critical features of workers' well-being (Cascales Mira 2021; Clark, D'Ambrosio and Zhu 2021; Gallie, Felstead and Green 2012). For instance, Clark, Kristensen and Westergård-Nielsen (2009) suggest that job satisfaction may be related to co-workers' wages, where the association may be both positive, as higher co-workers' wages may provide information about prospects (see also Javdani and Krauth 2020), but also negative if the worker's wage is below the median wage (Card et al. 2012). Job-position gender diversity is related to higher worker well-being (Clark, D'Ambrosio and Zhu 2021). To make things more complicated, the perception of what constitutes a "good job" is highly subjective, differing between genders, for instance (Kaufman and White 2015). Job attribute preferences reflect the desire for specific work-related outcomes and may also be diversified across other workers' characteristics, such as domestic circumstances, highest qualification held and occupation (Sutherland 2012).

The related economic literature has also attempted to evaluate the role of external global economic changes, such as production fragmentation across borders and technological progress. Vertical specialization, first quantified via offshoring indicators (Baumgarten, Geishecker and Görg 2013; Ebenstein et al. 2014; Egger, Kreickemeier and Wrona 2015) and recently by GVC measures based on global input–output data (Feenstra and Sasahara 2018; Parteka and Wolszczak-Derlacz 2019 and 2020), has been shown to have profound implications for labour markets. The literature is abundant, but many studies have assessed the phenomena in a purely economic way, based on information on wages (Baumgarten, Geishecker and Görg 2013; Ebenstein et al. 2014; Geishecker, Görg and Munch 2010; Parteka and Wolszczak-Derlacz 2019 and 2020; Shen and Silva 2018).[4] The use of wages as an

[4] A large body of related research deals with the effects of production fragmentation on employment and job displacement (Autor et al. 2014; Egger, Kreickemeier and Wrona 2015; Hummels, Munch and Xiang 2018) or labour market polarization (Cirillo 2018; Autor and Dorn 2013; Goos, Manning and Salomons 2014).

indicator of working conditions can be partially justified by the concept of social upgrading.[5] This reflects the improvement in workers' well-being resulting from involvement in global production (Milberg and Winkler 2011). However, the empirical literature on the broadly understood social consequences of trade and the proliferation of GVCs beyond wages gives contrasting results. Some empirical studies confirm a positive relationship, showing improvement in labour standards in companies that are more active in international trade (Nadvi et al. 2004; Bair and Gereffi 2001). Another strand of research finds that the link between economic and social upgrading is industry-specific (Bernhardt and Pollak 2016). Some authors claim that greater GVC involvement may not produce better pay or working conditions (Gimet, Guilhon and Roux 2015; Lee and Gereffi 2013; Lee, Gereffi and Lee 2016).

Moreover, the linkages between GVCs and non-monetary aspects of working conditions have mainly been analysed from the perspective of developing countries (Bair and Gereffi 2001; Barrientos et al. 2016; Kabeer and Mahmud 2004; Lee, Gereffi and Lee 2016; Rossi 2013). The question of how job quality varies among different groups of workers in developed countries is rarely raised in relation to GVCs and the existing evidence is mostly country- and industry-specific. For instance, Smith and Pickles (2015) find that in the Slovak clothing industry, wages and benefits in export-oriented companies may be higher, but employment stability is not. Lloyd and James (2008), in turn, report a positive impact of GVCs on the health and safety of workers employed in the UK food processing industry. Budría and Baleix (2020) investigate the effects of production fragmentation on individual job satisfaction and the perceived risk of job loss among German workers, finding that offshoring is negatively associated with job satisfaction. Studies on the production fragmentation–labour market nexus that offer a broader, cross-country perspective also tend to focus on wages as an indicator of labour conditions (Parteka and Wolszczak-Derlacz 2019 and 2020). Nikulin, Wolszczak-Derlacz and Parteka (2022) go one step further and examine how involvement in GVCs affects the wages, working hours and additional payments of workers from 24 European countries. Their results indicate a diversified effect of GVCs on working conditions, depending on the measure used: workers in sectors more deeply involved in GVCs have lower and less stable earnings, but they are also less likely to have to work overtime. The authors call for further research to consider diverse aspects of workers' well-being.

Another strand of related research deals with the worker-level effects of technological progress. It is widely recognized that rapid technological changes are closely linked to labour market outcomes, including wages and employment (for a review, see Georgieff 2024; Goos 2018). An influential stream of literature addresses the displacement effect, typical for highly routine jobs prone to computerization and robotization (Frey and Osborne 2017), and the degree of substitution between robots (automation) and workers (Acemoglu and Restrepo 2018 and 2020). According to the skill-based technological change and routine-based technological change hypotheses (Acemoglu and Autor 2011; Autor et al. 2003; Goos, Manning and Salomons 2014), low-skilled workers constitute the most vulnerable group, while highly skilled workers may benefit from new technologies.[6]

Existing studies show that the implications of the newest technologies are complex and differ from a simple case of replacing workers with machines. Digital technologies have important effects on workers' well-being, since they may put pressure on work–life balance or be the source of "technostress" (Tarafdar, Cooper and Stich 2019; Salanova, Llorens and Ventura 2014; Berg-Beckhoff, Nielsen and Ladekjær Larsen 2017). AI may impact human–machine interactions, resulting in new and changing work environments (Lane and Saint-Martin 2021), and affecting workers' well-being (Nazareno and Schiff 2021). Generative AI can have effects on both job quantity and job quality (Gmyrek, Berg and Bescond 2023).

[5] Social upgrading may be defined as "the process of improvement in the rights and entitlements of workers as social actors, which enhances the quality of their employment" (Barrientos, Gereffi and Rossi 2011, 324).

[6] For empirical evidence see, among others: Autor et al. (2003), Autor and Handel (2013), Autor and Dorn (2013), Frey and Osborne (2017) for the United States; and Goos, Manning and Salomons (2014), and Marcolin, Miroudot and Squicciarini (2016) for the European Union.

As regards the effects of technological progress on employment, the linkages depend on the suitability of job-related tasks for machine learning (Brynjolfsson and Mitchell 2017). The analysis conducted by Antón, Fernández-Macías and Winter-Ebmer (2020) reveals that robotization may be negatively associated with work intensity, whereas there is no linkage with the physical environment or skills and discretion dimensions of job quality. Turja et al. (2024) find that, on average, job satisfaction is lower in robotized workplaces than in non-robotized ones. In the case of AI technologies, the effects are not entirely related to the displacement effect, and for some workers these technologies may even be beneficial: in high-skill occupations, the role of AI solutions may be positive (Lane and Saint-Martin 2021, 23). Webb (2020) shows that, while exposure to robots and software is mainly typical for highly routine jobs, AI "performs tasks that involve detecting patterns, making judgments, and optimization" (Webb 2020, 3) – tasks typical of many high-skill occupations. Despite broad concerns about AI's potential to substitute for labour, Felten, Raj and Seamans (2019) show that, while exposure to AI is not significantly related to employment growth, it is positively correlated with wage growth. The recent evidence for Europe provided by Albanesi et al. (2023) suggests that AI may be related to employment growth, especially for skilled workers, but the effect on wages is rather negligible. Similarly, Acemoglu et al. (2022) find a significant employment surge in AI-exposed establishments, but no detectable effect in either employment or wages at the occupation or sector level. The authors argue that the effect of AI is limited because "AI technologies are still in their infancy" (Acemoglu et al. 2022, S337) and only a small part of the US economy is involved in AI-related tasks. The study conducted for Germany reveals a positive effect on wages from AI and a small but positive effect on wages from robotization (Grimm and Gathmann 2022). The newest evidence on the effect of generative AI shows a possible positive surge in productivity growth (Brynjolfsson, Li and Raymond 2023; Calvino and Fontanelli 2023).

Summarizing the empirical evidence on technology–wage links, the net result of automation on wages is ambiguous because of the two opposite effects: substitution and productivity. The final result depends on routinization (or skill) level (e.g. Acemoglu and Restrepo 2020; van der Velde 2020). Similarly, the empirical evidence on the impact of AI on wages is also rather mixed (for a review, see Georgieff 2024).

Overall, working conditions are not easy to quantify, given their multidimensional and highly intangible nature. One approach is based on composite indicators of job quality (for an overview, see Cascales Mira 2021). There are many indicators for job quality in Europe, proposed by the ILO, Eurostat and Eurofound (for a review, see, among others, Cazes, Hijzen and Saint-Martin 2015). They rely both on aggregate indices and individual aspects of job quality. For instance, the Job Quality Index developed by the European Trade Union Institute (ETUI) (see Leschke, Watt and Finn 2008) and calculated for European countries includes such aspects as: (i) wages; (ii) non-standard forms of employment; (iii) working time and work–life balance; (iv) working conditions and job security; (v) skills and career development; and (vi) collective interest representation. Periodically published EWCS reports (Eurofound 2017, 2020, 2021 and 2022) aim to capture the complexity of job quality and rely on indices for physical environment, work intensity, working time quality, social environment, skills and discretion, prospects and earnings. The EWCS is the primary source of data employed in the next section.

3. Data and empirical approach

3.1. Dataset

To find the linkages between working conditions, GVCs and digital technology, we use a rich dataset (described in table SA1 in the supplementary online appendix), merging the data from numerous sources and covering workers from 22 European countries.[7]

[7] Belgium, Bulgaria, Cyprus, Czechia, Estonia, France, Germany, Hungary, Italy, Latvia, Lithuania, Luxembourg, Malta, the Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Spain, Sweden and the United Kingdom.

Our approach enables a complex examination of workers' well-being: we employ six job quality EWCS indices (ranging from 0, the worst score, to 100, the best score) and compare them to wages. The job quality indices come from the 2015 EWCS and refer to six areas: physical environment (e.g. indicators of vibration, noise and temperature); work intensity (e.g. pace determinants and emotional demands); working time quality (e.g. working time arrangements and flexibility); social environment (e.g. social support and management quality); skills and discretion (e.g. training opportunities and decision latitude); and prospects (e.g. career prospects and job security).[8] Complementarily, we use information on average hourly wages, derived from the 2014 Structure of Earnings Survey (SES) as mean average gross hourly earnings in the reference month, converted into US dollars. Micro-level data are then matched with sector-level indicators of GVC involvement (based on the World Input–Output Database (WIOD); Timmer et al. 2015), expressed as the share of foreign value added (FVA) in exports (Wang, Wei and Zhu 2013). Theoretically, this indicator varies between 0 and 1 (where 1 indicates a total dependence of sectoral exports on FVA); in our sample, it varies between 0.01 and 0.7 (see table in the main appendix). Lastly, we match occupation-level indicators of exposure to technology, ranging from 0 to 100 (Webb 2020).[9] We use three occupational technological exposure measures related to robot, software and AI exposure, respectively. The scores reflect the intensity of patenting activity observed for each of these technologies in a given occupation.

3.2. Descriptive statistics

The summary statistics of all the variables are presented in the table in the main appendix. Our variables of interest, namely the job quality scores, are characterized by substantial variability. Given that we take into account six different job quality indices as well as monetary wages, it is important to consider their internal consistency and correlation. The association of the job quality indices from the EWCS with health and well-being has been tested, validating the use of six different measures for various dimensions of job quality.[10] We also find a weak correlation between wages and non-wage job quality indices, indicating that they do not capture the same features.[11]

A deeper illustration of job quality distribution is presented in figures SA1 and SA2 in the supplementary online appendix. They indicate that job quality varies both between and within countries in Europe. An analysis of the distribution of occupations across different technology measures (Webb 2020)[12] indicates that the potential impact of technologies is heterogeneous across occupations and different types of technology exposure.[13]

3.3. Model

Our key task is to estimate the intertwined relationship between different aspects of working conditions, the intensity of GVC involvement and the technological content of occupations. To this end, we run the following augmented Mincerian regression:

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

[8] For a detailed overview, see table SA3 in the supplementary online appendix.
[9] See table SA2 in the supplementary online appendix.
[10] For further details, see section 2 of Eurofound (2017).
[11] The value of the correlation coefficient is even close to zero in the case of working time quality or social environment – see table SA4 in supplementary online appendix.
[12] Albanesi et al. (2023) provide the statistics on technology content across countries, matching the data on employment with technological indicators from Webb (2020) for 16 European countries. They document an increase of employment shares in AI occupations (2011–19) matched with cross-country heterogeneity in AI employment patterns.
[13] See table SA3 in the supplementary online appendix.

where i stands for worker, o occupation, j company, s sector of employment, c country and k the type of job quality (JQ) EWCS index. As an alternative to JQ, we employ the log of wage. In JQ estimates (relying on EWCS data), the set of individual characteristics ($Worker_i$) includes sex, age, educational attainment and skills (four types, based on occupation). In the case of wage regression, based on more detailed SES data, $Worker_i$ characteristics include sex, age, educational attainment and type of employment (a full-time/part-time job binary variable). $Firm_j$ stands for firm-related job characteristics: in models using the EWCS indices, we use type of contract (unlimited/temporary) and type of employment (part-time or full-time); in wage regression, we use length of service in the enterprise, type of employment (full-time/part-time) and form of economic and financial control (public/private)[14]. Sector productivity ($Prod_s$, expressed in logs) is equal to the ratio of value added to the total number of hours worked by employees. GVC_{sc} is a proxy for country sector-specific involvement in GVCs, while $Tech_o$ refers to an occupation-level technology exposure measure. We also add the interaction between GVC and $Tech$, which takes into account the possibility that the effect of GVCs on working conditions depends on the type of technological exposure ($GVC_{sc} \times Tech_o$). The marginal effect of GVCs on job quality is equal to:

$$\frac{\delta JQ}{\delta GVC} = \beta_4 + \beta_6 Tech \tag{2}$$

This is similar for wages:

$$\frac{\delta \ln(wage)}{\delta GVC} = \beta_4 + \beta_6 Tech \tag{3}$$

and both can be represented graphically (see figures 1 and 2). Additionally, we include country and sector fixed effects: D_c should clear all country-specific characteristics such as labour market regulations, and D_s the remaining characteristics of sectors.

In the model using the job quality indices from the EWCS (in the range 0–1), equation (1) is estimated by fractional probit,[15] while in the wage-based model the equation is estimated using weighted ordinary least squares (OLS). Weights are calculated on the basis of the SES grossing-up factor adjusted to the number of observations per country (to ensure that each country is equally represented in the sample). Regressions for both types of dependent variable are estimated with robust standard errors clustered at the country-sector level.

In the next section, we present the estimation results for the EWCS indices (section 4.1) and wages (section 4.2).

4. Results

4.1. Working conditions measured by job quality indices (EWCS)

The estimation results for equation (1) obtained with six different job quality indices from the EWCS and three types of technological exposure are presented in tables 1–3 (the tables report only the key coefficients, while full results are shown in tables SA5–SA7 in the supplementary online appendix). Table 1 refers to technological exposure (*Tech*) measured as software exposure, while tables 2 and 3 refer to robot and AI exposure, respectively.

[14] The distinction between private and public entities is not captured by sectoral fixed effects. We have excluded purely public sectors, such as the armed forces, from the analysis. In other sectors, both public and private companies are present: overall, 58.54 per cent of companies in the SES are private and 41.46 per cent public.

[15] We use the command *fracreg* in Stata. In case of fractional probit, we do not report the pseudo R^2, as it should be interpreted with great caution (Long and Freese 2006).

Table 1. Determinants of job quality EWCS indices – *Tech* measured as software exposure

	Dependent variable: Job quality EWCS indices					
	Social environment	Skills and discretion	Physical environment	Work intensity	Prospects	Working time
GVC	0.625*** (0.136)	0.322 (0.237)	0.602*** (0.198)	−0.004 (0.128)	0.085 (0.107)	0.332** (0.164)
Tech	0.001 (0.000)	0.001 (0.001)	−0.003*** (0.001)	0.001* (0.000)	0 (0.000)	0 (0.000)
GVC × *Tech*	−0.013*** (0.002)	−0.002 (0.004)	−0.014*** (0.003)	−0.001 (0.002)	−0.004** (0.002)	−0.006** (0.003)
N	22 524	22 350	22 523	22 478	22 521	22 524

*, ** and *** indicate statistical significance at the 10, 5 and 1 per cent levels, respectively.
Notes: Estimation method: fractional probit. We include personal characteristics, specifically sex, age, education, skills, type of contract and part-time employment. Country and sector fixed effects included. Robust standard errors appear in parentheses, clustered at the country-sector level.
Source: Our own calculation based on data from the EWCS and WIOD, and Webb (2020).

Table 2. Determinants of job quality EWCS indices – *Tech* measured as robot exposure

	Dependent variable: Job quality EWCS indices					
	Social environment	Skills and discretion	Physical environment	Work intensity	Prospects	Working time
GVC	0.548*** (0.121)	0.332* (0.189)	0.559*** (0.175)	−0.129 (0.101)	0.092 (0.104)	0.097 (0.136)
Tech	−0.001*** (0.000)	0 (0.001)	−0.007*** (0.001)	0.001* (0.000)	0 (0.000)	−0.002*** (0.000)
GVC × *Tech*	−0.012*** (0.002)	−0.003 (0.003)	−0.013*** (0.003)	0.002 (0.002)	−0.004*** (0.002)	−0.001 (0.002)
N	22 524	22 350	22 523	22 478	22 521	22 524

*, ** and *** indicate statistical significance at the 10, 5 and 1 per cent levels, respectively.
Note: See notes in table 1.
Source: Our own calculation based on data from the EWCS and WIOD, and Webb (2020).

Table 3. Determinants of job quality EWCS indices – *Tech* measured as AI exposure

	Dependent variable: Job quality EWCS indices					
	Social environment	Skills and discretion	Physical environment	Work intensity	Prospects	Working time
GVC	0.042 (0.147)	0.164 (0.253)	−0.018 (0.166)	0.122 (0.131)	−0.053 (0.115)	0.353*** (0.125)
Tech	0 (0.001)	0.001* (0.001)	−0.004*** (0.001)	0.001*** (0.000)	0 (0.000)	0.001* (0.000)
GVC × *Tech*	0 (0.002)	0.001 (0.004)	−0.002 (0.003)	−0.003 (0.002)	−0.001 (0.002)	−0.006*** (0.002)
N	22 524	22 350	22 523	22 478	22 521	22 524

*, ** and *** indicate statistical significance at the 10, 5 and 1 per cent levels, respectively.
Note: See notes in table 1.
Source: Our own calculation based on data from the EWCS and WIOD, and Webb (2020).

Since we use the fractional probit model (the job quality indices are in the range (0,1)), the parameters provide only the sign of the marginal effect of the covariates on the outcome, but the magnitude is difficult to interpret (Papke and Wooldridge 1996; Wooldridge 2010). Accordingly, we provide the average marginal effects in table 4: the association between GVCs and working conditions is not large, between −0.1 to 6 per cent. In other words, a small change in the intensity of GVC involvement can increase working conditions by up to 6 per cent in the case of the skills and discretion dimension of job quality, which is generally higher for managers and professionals.[16] However, the link is not positive for all types of working conditions, such as work intensity.

Table 4. Determinants of job quality EWCS indices – Marginal effects

	Social environment	Skills and discretion	Physical environment	Work intensity	Prospects	Working time
Software exposure						
GVC	0.027 (0.026)	0.064 (0.040)	−0.014 (0.023)	−0.011 (0.025)	−0.031 (0.026)	0.021 (0.030)
Robot exposure						
GVC	−0.001 (0.028)	0.059 (0.040)	−0.029 (0.023)	−0.011 (0.026)	−0.04 (0.026)	0.013 (0.027)
AI exposure						
GVC	0.009 (0.027)	0.059 (0.042)	−0.023 (0.021)	−0.004 (0.026)	−0.034 (0.026)	0.029 (0.027)

Note: Robust standard errors clustered at the country-sector level.
Source: Our own calculation based on data from the EWCS and WIOD, and Webb (2020).

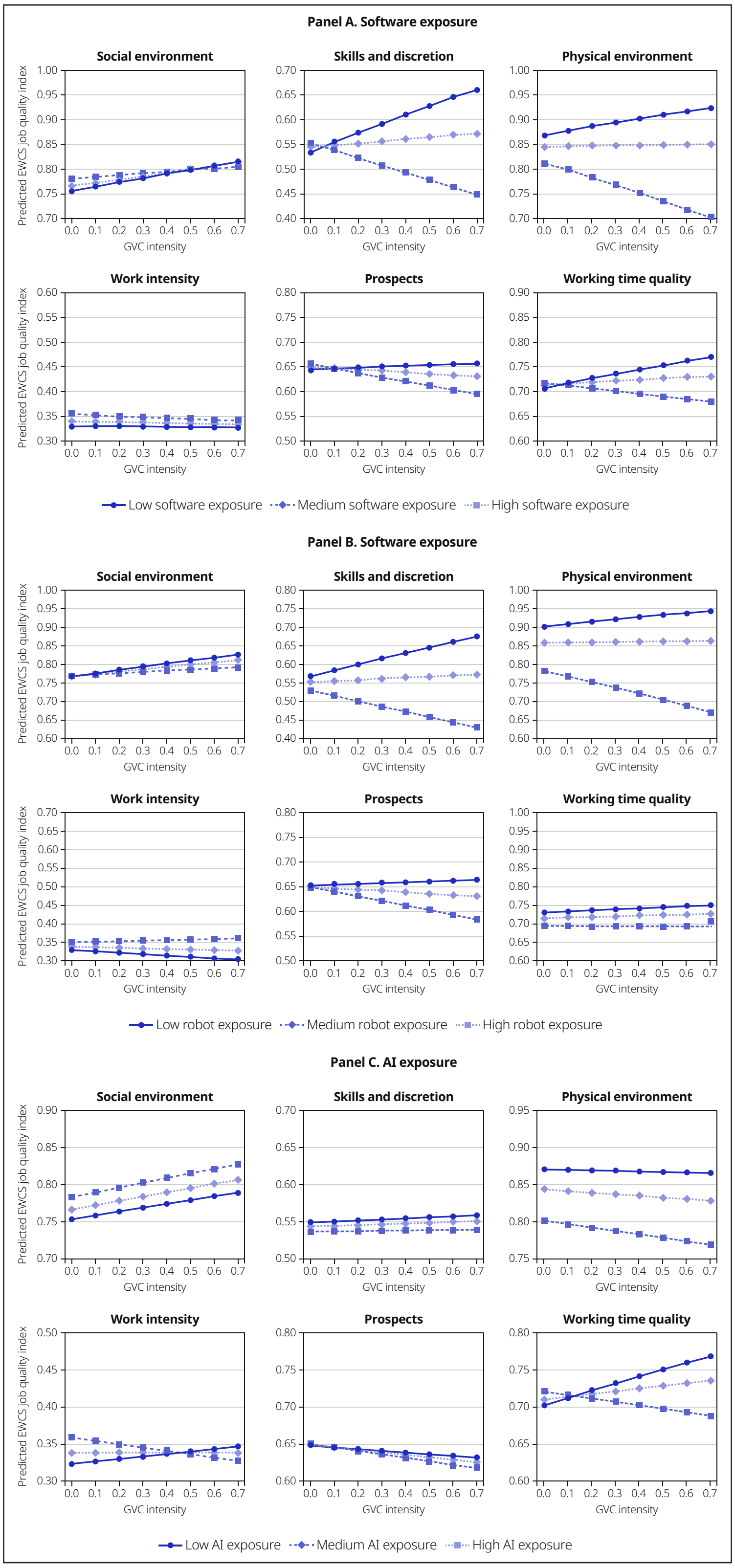
We are mainly interested in variables *GVC*, *Tech* and the interaction term between them. Generally speaking, the relationship between GVC intensity and aspects of job quality such as the social and physical environment is positive (tables 1 and 2), but this is not the case once we consider the exposure to AI technologies, where the relationship between job quality and GVCs is mostly not statistically significant (table 3).

If the coefficient for the interaction term is statistically significant, then the relationship between GVCs and job quality depends, at least in statistical terms, on the degree of technological exposure. Figure 1 depicts the relationship between GVCs and predicted job quality indices at low, medium and high levels of software, robot and AI exposure. In each of the graphs, the relative position of the three lines reflects the general differences in job quality across occupations that differ in technological exposure, while the inclination of the lines shows the effect of an increase in GVC intensity.

In most cases, the differences across technological levels are small (the lines overlap) and, if observed, refer to selected aspects of job quality. Concerning the interacting effects of technological exposure on the GVC–job quality relationship, the picture is mixed. In occupations highly exposed to software and robots (figure 1, panels A and B), dimensions of job quality such as physical environment, skills and discretion or prospects worsen with the intensification of GVC involvement. The reverse is true for occupations with less exposure to software and robots, especially in the case of physical environment, and skills and discretion. However, this does not really mean that technological factors significantly (also in economic terms) alter the core relationship between job quality and GVCs, since the

[16] See figure SA2 in the supplementary online appendix.

Figure 1. Predicted job quality EWCS indices due to changes in GVCS, at different levels of technological exposure of jobs (illustrating the results from tables 1–3)



Notes: The lines on the chart correspond to technological exposure level. Division of occupations into categories of low/medium/high exposure according to the index values (low = 10, medium = 40, high = 80).

Source: Our own calculation based on data from the EWCS and WIOD, and Webb (2020).

magnitude of the predicted changes (note the scale of the y-axis) indicates that the effects of the interaction are very small. This is also visible in the case of AI technologies (figure 1, panel C): the changes in most aspects of job quality associated with an intensification of GVC involvement are similar for occupations with different levels of AI exposure, and they are minor in magnitude.

The results for the control variables (tables SA5–SA7 in the supplementary online appendix) confirm the importance of workers' individual characteristics. We find a higher probability of improvement in social environment for male workers (the same effect is observed for prospects and work intensity, lower work intensity implying better working conditions). Female workers are better off in terms of physical environment and working time. Younger workers are more likely to face worse conditions in terms of physical environment, work intensity and working time, but enjoy better prospects. Workers aged 30–49 are better off than older workers with respect to social environment and prospects, while the opposite is true for other job quality indices. As regards education variables, we compare employees with low and medium levels of education with employees with higher education. Workers with low and medium levels of education have worse working conditions, except in terms of work intensity and working time. As far as skills are concerned, workers with higher education may benefit from such aspects of job quality as social environment, skills and discretion, physical environment and prospects. The opposite is the case for work intensity and working time. Workers with unlimited contracts are more likely to experience higher job quality in most aspects. Those working part-time are better off as far as physical environment, work intensity and working time are concerned.

4.2. Working conditions measured by information on wages

We now turn to a similar analysis, this time based on wages as a proxy for working conditions. The estimation results are presented in table 5. Wages are negatively related to the intensification of links to GVCs. We estimate the OLS regression using log wages to allow an interpretation of negative coefficients as quasi elasticities: a 1-percentage-point rise in the intensity of involvement in GVCs is associated with a drop in wages of 3.6 to 4.6 per cent. This finding is in line with papers that document an inverse (but weak) relationship between the strength of GVC links/offshoring and the wages of European workers (Baumgarten, Geishecker and Görg 2013; Parteka and Wolszczak-Derlacz 2019; Nikulin, Wolszczak-Derlacz and Parteka 2022).

Table 5. Determinants of wages

	Dependent variable: Log of wage		
	Software exposure	Robot exposure	AI exposure
GVC	−0.361** (0.150)	−0.456*** (0.127)	−0.401*** (0.154)
Tech	−0.002*** (0.001)	−0.007*** (0.000)	0.004*** (0.001)
GVC × Tech	0.005* (0.003)	0.007*** (0.002)	0.004* (0.002)
R^2	0.8	0.82	0.81
N	9 218 140	9 218 140	9 218 140

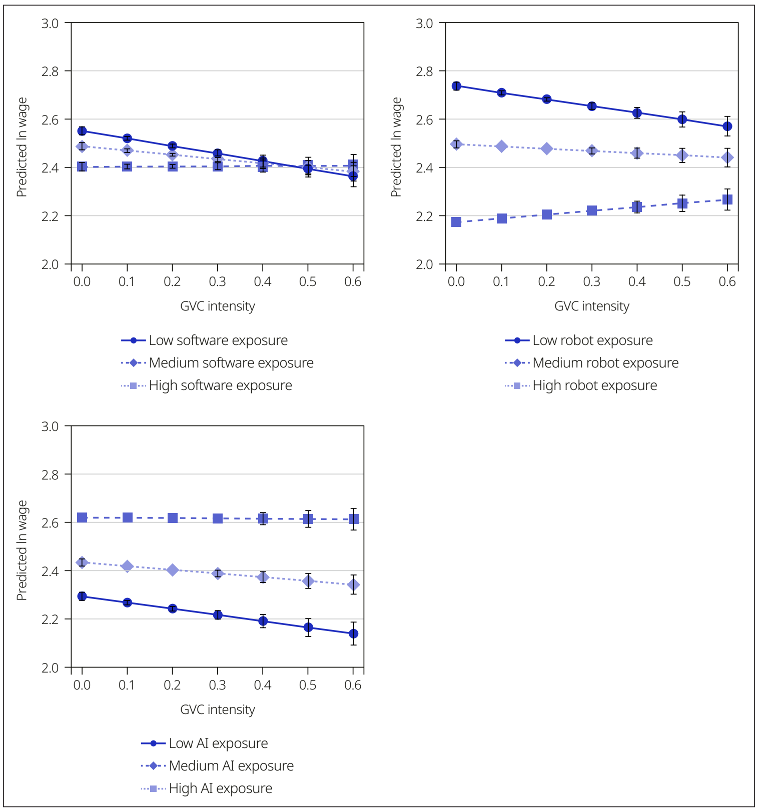
*, ** and *** indicate statistical significance at the 10, 5 and 1 per cent levels, respectively.

Notes: We include personal and firm characteristics, specifically sex, age, education, full/part-time employment, duration of experience in the unit and public/private company. Country and sector fixed effects included. Robust standard errors appear in parentheses, clustered at the country-sector level.

Source: Our own calculation based on data from the SES and WIOD, and Webb (2020).

The conditional effect, interacting GVC intensity with technology exposure, is very weak. Figure 2 illustrates these results, presenting the predicted log wages due to changes in GVC intensity at the different levels of technological exposure of jobs (low, medium or high). The results show that, on average, jobs with lower levels of software or robot exposure have slightly higher wages, but that these decrease as GVC links intensify. Notably, the changes in average wages at different levels of software and robot exposure are small. At the same time, wages in occupations highly exposed to robots or software do not change significantly with increasing intensity in GVC involvement. In AI-exposed jobs, the relationship seems to be even more stable: wages are higher in jobs highly exposed to AI but remain largely stable with increasing GVC involvement intensity. Shifts in wages for jobs with low and medium AI exposure are also very small. Our results confirm the recent evidence on the small impact of AI on wage determination provided by Acemoglu et al. (2022), Albanesi et al. (2023) and Milanez (2023).[17]

Figure 2. Predicted log wages due to the changes in GVC intensity at different levels of technological exposure of jobs (illustrating the results from table 4)



Notes: The lines on the chart correspond to the technological exposure. Division of occupations into low/medium/high software, robot and AI exposure according to the index values (low = 10, medium = 40, high = 80).

Source: Our own calculations based on job quality indices from the 2015 EWCS merged with the 2014 SES, the 2016 WIOD and technological exposure indicators from Webb (2020).

4.3. Robustness checks

In order to check the sensitivity of the results, we run numerous robustness checks (presented in the supplementary online appendix). We start with the sensitivity analysis for wages. First, we consider cross-country differences in labour market institutional coordination, specifically wage-bargaining schemes. The data are drawn from the database

[17] Full results are reported in table SA8 in the supplementary online appendix. Generally, men, younger workers and those with lower levels of education and less experience, working part-time earn lower wages.

on Institutional Characteristics of Trade Unions, Wage Setting, State Intervention and Social Pacts (ICTWSS) (Visser 2019). We take into account the recoded variable of the coordination of wage-setting (*coord*), where 1 denotes centralized or industry-level bargaining and 0 indicates countries with mixed industry- and firm-level bargaining (table SA9). Then we employ the variables *GOC*[18] (general opening clauses in collective agreement) and wage bargaining (*barg*3[19]) (tables SA10 and SA11). Additionally, we add country-level variables, such as import and export share of gross domestic product (GDP) as measures of trade openness (tables SA12 and SA13). The baseline results are not altered by augmenting the regression either by variables describing wage-setting mechanism or by country-specific openness measures.

Next, we change the measure of GVC intensity, substituting FVA share in exports with global import intensity of production, as defined by Timmer et al. (2016). Global import intensity is based on the ratio of all intermediate imports added along the entire chain (not only the previous stage) to the value of the final product. Our main results hold (see table SA14).

Then we substitute Webb's index of AI exposure with the AI Occupational Impact (AIOI) index from Felten, Raj and Seamans (2018 and 2019). Wages are higher for workers with greater exposure to AI and they do change with the rise of GVC participation (table SA15). In line with previous studies (e.g. Felten, Raj and Seamans 2019), we generally find that AI-exposed occupations are characterized by positive (minor) changes in wages. Lastly, we add the size of the company as the additional covariate (table SA16).[20]

We repeat the same robustness checks for all EWCS job quality indices (tables SA17–SA35) and our main findings are confirmed.

5. Conclusions

A comprehensive view of the joint impact of the production internationalization and digital progress on job quality and social conditions at work is still lacking, including in the European context. The purpose of our analysis in this article was to shed new light on the differences in working conditions across Europe. In particular, we aimed to broaden the understanding of Europeans' well-being at work by: (i) using a multidimensional approach to the quantification of working conditions (analysing wages and several aspects of job quality); and (ii) jointly assessing the role played by the dependence of European labour markets on GVCs and various types of digital technologies.

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

Concerning the second point, we were particularly interested in examining how the two global phenomena of intensification of cross-border production links and rapid

[18] Agreements containing general opening clauses (renegotiation of contractual provisions at lower levels, under specified conditions) = 1 and agreements containing no opening clauses = 0.

[19] The predominant level at which wage bargaining generally takes place: 1 = local or company level; 2 = industry level; and 3 = central level.

[20] There is no information about company sizes for Cyprus, Luxembourg and Malta.

progress in digital technologies affect job quality (compared to wages). We have estimated several econometric models linking wages and six job quality indices from the EWCS with GVC intensity and the technological characteristics of workers' occupations (and several additional controls). We have thus combined three important perspectives present in the related literature: (i) labour economics/sociological research on working conditions and decent work; (ii) international economic studies on production fragmentation; and (iii) the literature on the labour market effects of technological progress driven by digital solutions.

We find that on average (that is, when controlling for individual and firm characteristics), involvement in GVCs correlates negatively with wages and (slightly) positively with some non-monetary aspects of job quality, once we consider the exposure of jobs to software or robots. When we consider the exposure of jobs to AI, the effect of the intensification of GVC involvement is negative for wages, but insignificant for the job quality indices. We thus find that the influence of GVCs on wages and different types of job quality measures may vary. This calls for an analysis of non-wage aspects in addition to wages themselves. Importantly, we find that technological factors do not alter the core relationship between global production links and job quality and wages in an economically meaningful way.

Our approach addresses the problem of a proper quantification of worker-level effects of global production fragmentation. Real-world problems of work overload, technostress and bad social or physical work environments cannot be solved without identifying their sources. Our analysis indicates that the information contained in input–output tables, once matched with detailed micro-level data on job quality, provides a fuller view of how GVCs impact workers. We hope that our results, exploring heterogeneity across countries, sectors, occupations and workers, convincingly confirm the multidimensional nature of working conditions. They are relevant to the formulation of adequate and coordinated policy responses to worsening labour standards due to pressure from cross-border competition, such as through GVCs, and the challenges resulting from rapid digital progress. Fair and high-quality job standards are of the highest priority because health problems and worsening job performance caused by bad working conditions require policy intervention.

We deliver empirical evidence on the impact of new types of technology, contributing to the growing body of literature on linkages between digital technology and labour markets. On the one hand, a recent survey among workers and employers in Europe revealed relatively positive expectations regarding the impact of AI on the labour market and working conditions (Lane, Williams and Broecke 2023). On the other hand, and as our study confirms, empirical evidence on the effects of digital technology on wages is highly inconclusive.

Our study is based on pre-pandemic data. Accordingly, the next important question that needs to be addressed is how the COVID-19 pandemic and changes in the world of work in its aftermath have affected job quality. The impact is also likely to have been unevenly distributed across workers. During the pandemic, some, such as healthcare workers, worked on the front line, while others had to close their businesses, and many of those working at home faced increased stress and pressure on their work–life balance; all experienced day-to-day uncertainty. These effects have had direct and indirect impacts on working practices and conditions in the post-pandemic landscape. Future research describing the impact of the pandemic on workers' well-being is thus needed.

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Competing interests

The authors declare that they have no competing interests.

References

Acemoglu, Daron, and David Autor. 2011. “Skills, Tasks and Technologies: Implications for Employment and Earnings”. In *Handbook of Labor Economics*, Vol. 4B, edited by Orley Ashenfelter and David Card, 1043–1171. Amsterdam: Elsevier.

Acemoglu, Daron, David Autor, Jonathon Hazell, and Pascual Restrepo. 2022. “Artificial Intelligence and Jobs: Evidence from Online Vacancies”. *Journal of Labor Economics* 40 (S1): S293–S340. https://doi.org/10.1086/718327.

Acemoglu, Daron, and Pascual Restrepo. 2018. “The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment”. *American Economic Review* 108 (6): 1488–1542. https://doi.org/10.1257/aer.20160696.

———. 2020. “Robots and Jobs: Evidence from US Labor Markets”. *Journal of Political Economy* 128 (6): 2188–2244. https://doi.org/10.1086/705716.

Aghion, Philippe, Benjamin F. Jones, and Charles I. Jones. 2019. “Artificial Intelligence and Economic Growth”. In *The Economics of Artificial Intelligence: An Agenda*, edited by Ajay Agrawal, Joshua Gans and Avi Goldfarb, 237–290. Chicago, IL: University of Chicago Press.

Agrawal, Ajay, Joshua S. Gans, and Avi Goldfarb. 2019. “Artificial Intelligence: The Ambiguous Labor Market Impact of Automating Prediction”. *Journal of Economic Perspectives* 33 (2): 31–50. https://doi.org/10.1257/jep.33.2.31.

Albanesi, Stefania, António Dias da Silva, Juan F. Jimeno, Ana Lamo, and Alena Wabitsch. 2023. “New Technologies and Jobs in Europe”. NBER Working Paper No. 31357. Cambridge, MA: National Bureau of Economic Research.

Aleksynska, Mariya. 2018. “Temporary Employment, Work Quality, and Job Satisfaction”. *Journal of Comparative Economics* 46 (3): 722–735. https://doi.org/10.1016/j.jce.2018.07.004.

Antón, José-Ignacio, Enrique Fernández-Macías, and Rudolf Winter-Ebmer. 2020 “Does Robotization Affect Job Quality? Evidence from European Regional Labour Markets”. IZA Discussion Paper No. 13975. Bonn: Institute of Labor Economics.

Autor, David H., and David Dorn. 2013. “The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market”. *American Economic Review* 103 (5): 1553–1597. https://doi.org/10.1257/aer.103.5.1553.

Autor, David H., David Dorn, Gordon H. Hanson, and Jae Song. 2014. “Trade Adjustment: Worker-Level Evidence”. *Quarterly Journal of Economics* 129 (4): 1799–1860. https://doi.org/10.1093/qje/qju026.

Autor, David H., and Michael J. Handel. 2013. “Putting Tasks to the Test: Human Capital, Job Tasks, and Wages”. *Journal of Labor Economics* 31 (S1): S59–S96. https://doi.org/10.1086/669332.

Autor, David H., Frank Levy, and Richard J. Murnane. 2003. “The Skill Content of Recent Technological Change: An Empirical Exploration”. *Quarterly Journal of Economics* 118 (4): 1279–1333. https://doi.org/10.1162/003355303322552801.

Badri, Adel, Bryan Boudreau-Trudel, and Ahmed Saâdeddine Souissi. 2018. "Occupational Health and Safety in the Industry 4.0 Era: A Cause for Major Concern?" *Safety Science* 109 (November): 403–411. https://doi.org/10.1016/j.ssci.2018.06.012.

Bair, Jennifer, and Gary Gereffi. 2001. "Local Clusters in Global Chains: The Causes and Consequences of Export Dynamism in Torreon's Blue Jeans Industry". *World Development* 29 (11): 1885–1903. https://doi.org/10.1016/S0305-750X(01)00075-4.

Baldwin, Richard. 2013. "Global Supply Chains: Why They Emerged, Why They Matter, and Where They Are Going". In *Global Value Chains in a Changing World*, edited by Deborah K. Elms and Patrick Low, 13–59. Geneva: World Trade Organization.

Barrientos, Stephanie, Gary Gereffi, and Arianna Rossi. 2011. "Economic and Social Upgrading in Global Production Networks: A New Paradigm for a Changing World". *International Labour Review* 150 (3–4): 319–340. https://doi.org/10.1111/j.1564-913X.2011.00119.x.

Barrientos, Stephanie, Peter Knorringa, Barbara Evers, Margareet Visser, and Maggie Opondo. 2016. "Shifting Regional Dynamics of Global Value Chains: Implications for Economic and Social Upgrading in African Horticulture". *Environment and Planning A* 48 (7): 1266–1283. https://doi.org/10.1177/0308518X15614416.

Baumgarten, Daniel, Ingo Geishecker, and Holger Görg. 2013. "Offshoring, Tasks, and the Skill–Wage Pattern". *European Economic Review* 61 (July): 132–152. https://doi.org/10.1016/j.euroecorev.2013.03.007.

Berg-Beckhoff, Gabriele, Grace Nielsen, and Eva Ladekjær Larsen. 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. https://doi.org/10.1080/10773525.2018.1436015.

Berliner, Daniel, Anne Regan Greenleaf, Milli Lake, Margaret Levi, and Jennifer Noveck. 2015. "Governing Global Supply Chains: What We Know (and Don't) about Improving Labor Rights and Working Conditions". *Annual Review of Law and Social Science* 11 (November): 193–209. https://doi.org/10.1146/annurev-lawsocsci-120814-121322.

Bernhardt, Thomas, and Ruth Pollak. 2016. "Economic and Social Upgrading Dynamics in Global Manufacturing Value Chains: A Comparative Analysis". *Environment and Planning A* 48 (7): 1220–1243. https://doi.org/10.1177/0308518X15614683.

Bonhomme, Stéphane, and Grégory Jolivet. 2009. "The Pervasive Absence of Compensating Differentials". *Journal of Applied Econometrics* 24 (5): 763–795. https://doi.org/10.1002/jae.1074.

Briken, Kendra, Shiona Chillas, Martin Krzywdzinski, and Abigail Marks. 2017. "Labour Process Theory and the New Digital Workplace". In *The New Digital Workplace: How New Technologies Revolutionise Work*, edited by Kendra Briken, Shiona Chillas, Martin Krzywdzinski and Abigail Marks, 1–17. London: Palgrave Macmillan.

Brynjolfsson, Erik, Danielle Li, and Lindsey R. Raymond. 2023. "Generative AI at Work". NBER Working Paper No. 31161. Cambridge, MA: National Bureau of Economic Research.

Brynjolfsson, Erik, and Tom Mitchell. 2017. "What Can Machine Learning Do? Workforce Implications". *Science* 358 (6370): 1530–1534. https://doi.org/10.1126/science.aap8062.

Brynjolfsson, Erik, Tom Mitchell, and Daniel Rock. 2018. "What Can Machines Learn, and What Does It Mean for Occupations and the Economy?" *AEA Papers and Proceedings* 108 (May): 43–47. https://doi.org/10.1257/pandp.20181019.

Budría, Santiago, and Juliette Milgram Baleix. 2020. "Offshoring, Job Satisfaction and Job Insecurity". *Economics* 14 (2020-23): 1–32. https://doi.org/10.5018/economics-ejournal.ja.2020-23.

Calvino, Flavio, and Luca Fontanelli. 2023. "A Portrait of AI Adopters across Countries: Firm Characteristics, Assets' Complementarities and Productivity". OECD Science, Technology and Industry Working Papers, No. 2023/02. Paris: OECD.

Card, David, Alexandre Mas, Enrico Moretti, and Emmanuel Saez. 2012. "Inequality at Work: The Effect of Peer Salaries on Job Satisfaction". *American Economic Review* 102 (6): 2981–3003. https://doi.org/10.1257/aer.102.6.2981.

Cascales Mira, María. 2021. "New Model for Measuring Job Quality: Developing an European Intrinsic Job Quality Index (EIJQI)". *Social Indicators Research* 155 (2): 625–645. https://doi.org/10.1007/s11205-021-02615-9.

Cazes, Sandrine, Alexander Hijzen, and Anne Saint-Martin. 2015. "Measuring and Assessing Job Quality: The OECD Job Quality Framework". OECD Social, Employment and Migration Working Papers, No. 174. Paris: OECD.

Cirillo, Valeria. 2018. "Job Polarization in European Industries". *International Labour Review* 157 (1): 39–63. https://doi.org/10.1111/ilr.12033.

Clark, Andrew E. 2015. "What Makes a Good Job? Job Quality and Job Satisfaction". *IZA World of Labor*, Article No. 215. https://doi.org/10.15185/izawol.215.

Clark, Andrew E., Conchita D'Ambrosio, and Rong Zhu. 2021. "Job Quality and Workplace Gender Diversity in Europe". *Journal of Economic Behavior & Organization* 183 (March): 420–432. https://doi.org/10.1016/j.jebo.2021.01.012.

Clark, Andrew E., Nicolai Kristensen, and Niels Westergård-Nielsen. 2009. "Job Satisfaction and Co-Worker Wages: Status or Signal?" *Economic Journal* 119 (536): 430–447. https://doi.org/10.1111/j.1468-0297.2008.02236.x.

Decancq, Koen, Marc Fleurbaey, and Erik Schokkaert. 2015. "Happiness, Equivalent Incomes and Respect for Individual Preferences". *Economica* 82 (S1): 1082–1106. https://doi.org/10.1111/ecca.12152.

Delautre, Guillaume, Elizabeth Echeverría Manrique, and Colin Fenwick, eds. 2021. *Decent Work in a Globalized Economy: Lessons from Public and Private Initiatives*. Geneva: ILO.

Deshpande, Advait, Natalie Picken, Linda Kunertova, Annemari De Silva, Giulia Lanfredi, and Joanna Hofman. 2021. *Improving Working Conditions Using Artificial Intelligence*. Luxembourg: Policy Department for Economic, Scientific and Quality of Life Policies, European Parliament.

Ebenstein, Avraham, Ann Harrison, Margaret McMillan, and Shannon Phillips. 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. https://doi.org/10.1162/REST_a_00400.

Egger, Hartmut, Udo Kreickemeier, and Jens Wrona. 2015. "Offshoring Domestic Jobs". *Journal of International Economics* 97 (1): 112–125. https://doi.org/10.1016/j.jinteco.2015.03.010.

Eurofound (European Foundation for the Improvement of Living and Working Conditions). 2017. *Sixth European Working Conditions Survey: Overview Report (2017 Update)*. Luxembourg: Publications Office of the European Union.

———. 2020. *Working Conditions in Sectors*. Luxembourg: Publications Office of the European Union.

———. 2021. *Working Conditions and Sustainable Work: An Analysis Using the Job Quality Framework*. Luxembourg: Publications Office of the European Union.

———. 2022. *Working Conditions in the Time of COVID-19: Implications for the Future*. Luxembourg: Publications Office of the European Union.

Felten, Edward W., Manav Raj, and Robert Seamans. 2018. “A Method to Link Advances in Artificial Intelligence to Occupational Abilities”. *AEA Papers and Proceedings* 108 (May): 54–57. https://doi.org/10.1257/pandp.20181021.

———. 2019. “The Occupational Impact of Artificial Intelligence: Labor, Skills, and Polarization”. Working Paper available at SSRN. http://dx.doi.org/10.2139/ssrn.3368605.

Feenstra, Robert C., and Akira Sasahara. 2018. “The ‘China Shock’, Exports and US Employment: A Global Input–Output Analysis”. *Review of International Economics* 26 (5): 1053–1083. https://doi.org/10.1111/roie.12370.

Fernández, Rosa M., and Christophe J. Nordman. 2009. “Are There Pecuniary Compensations for Working Conditions?” *Labour Economics* 16 (2): 194–207. https://doi.org/10.1016/j.labeco.2008.08.001.

Fleurbaey, Marc. 2015. “Beyond Income and Wealth”. *Review of Income and Wealth* 61 (2): 199–219. https://doi.org/10.1111/roiw.12187.

Frey, Carl Benedikt, and Michael A. Osborne. 2017. “The Future of Employment: How Susceptible Are Jobs to Computerisation?” *Technological Forecasting and Social Change* 114 (January): 254–280. https://doi.org/10.1016/j.techfore.2016.08.019.

Gallie, Duncan, Alan Felstead, and Francis Green. 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. https://doi.org/10.1177/0950017012451633.

Gandini, Alessandro. 2019. “Labour Process Theory and the Gig Economy”. *Human Relations* 72 (6): 1039–1056. https://doi.org/10.1177/0018726718790002.

Geishecker, Ingo. 2012. “Simultaneity Bias in the Analysis of Perceived Job Insecurity and Subjective Well-Being”. *Economics Letters* 116 (3): 319–321. https://doi.org/10.1016/j.econlet.2012.03.018.

Geishecker, Ingo, Holger Görg, and Jacob Roland Munch. 2010. “Do Labour Market Institutions Matter? Micro-Level Wage Effects of International Outsourcing in Three European Countries”. *Review of World Economics* 146 (1): 179–198. https://doi.org/10.1007/s10290-009-0039-9.

Georgieff, Alexandre. 2024. “Artificial Intelligence and Wage Inequality”. OECD Artificial Intelligence Papers, No. 13. Paris: OECD.

Gimet, Céline, Bernard Guilhon, and Nathalie Roux. 2015. “Social Upgrading in Globalized Production: The Case of the Textile and Clothing Industry”. *International Labour Review* 154 (3): 303–327. https://doi.org/10.1111/j.1564-913X.2015.00244.x.

Gmyrek, Paweł, Janine Berg, and David Bescond. 2023. “Generative AI and Jobs: A Global Analysis of Potential Effects on Job Quantity and Quality”. ILO Working Paper No. 96. Geneva: ILO.

Goos, Maarten. 2018. “The Impact of Technological Progress on Labour Markets: Policy Challenges”. *Oxford Review of Economic Policy* 34 (3): 362–375. https://doi.org/10.1093/oxrep/gry002.

Goos, Maarten, Alan Manning, and Anna Salomons. 2014. “Explaining Job Polarization: Routine-Biased Technological Change and Offshoring”. *American Economic Review* 104 (8): 2509–2526. https://doi.org/10.1257/aer.104.8.2509.

Grimm, Felix, and Christina Gathmann. 2022. “The Diffusion of Digital Technologies and Its Consequences in the Labor Market”, Paper presented at the Vereins für Socialpolitik Annual Conference 2022: Big Data in Economics, Basel, September 2022.

Harley, Bill. 2018. "Sociology, the Labour Process and Employment Relations". In *The Routledge Companion to Employment Relations*, edited by Adrian Wilkinson, Tony Dundon, Jimmy Donaghey and Alexander J.S. Colvin, 81–92. Abingdon: Routledge.

Hernandez, Danny, and Tom B. Brown. 2020. "Measuring the Algorithmic Efficiency of Neural Networks", arXiv:2005.04305. https://doi.org/10.48550/arXiv.2005.04305.

Hummels, David, Jacob R. Munch, and Chong Xiang. 2018. "Offshoring and Labor Markets". *Journal of Economic Literature* 56 (3): 981–1028. https://doi.org/10.1257/jel.20161150.

Javdani, Mohsen, and Brian Krauth. 2020. "Job Satisfaction and Co-Worker Pay in Canadian Firms". *Canadian Journal of Economics/Revue canadienne d'économique* 53 (1): 212–248. https://doi.org/10.1111/caje.12422.

Kabeer, Naila, and Simeen Mahmud. 2004. "Globalization, Gender and Poverty: Bangladeshi Women Workers in Export and Local Markets". *Journal of International Development* 16 (1): 93–109. https://doi.org/10.1002/jid.1065.

Karasek, Robert, and Töres Theorell. 1990. *Healthy Work: Stress, Productivity, and the Reconstruction of Working Life*. New York, NY: Basic Books.

Kaufman, Gayle, and Damian White. 2015. "What Makes a "Good Job"? Gender Role Attitudes and Job Preferences in Sweden". *Gender Issues* 32 (4): 279–294. https://doi.org/10.1007/s12147-015-9145-2.

Lane, Marguerita, and Anne Saint-Martin. 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. Paris: OECD.

Lane, Marguerita, Morgan Williams, and Stijn Broecke. 2023. "The Impact of AI on the Workplace: Main Findings from the OECD AI Surveys of Employers and Workers". OECD Social, Employment and Migration Working Papers, No. 288. Paris: OECD.

Lee, Joonkoo, and Gary Gereffi. 2013. "The Co-Evolution of Concentration in Mobile Phone Global Value Chains and Its Impact on Social Upgrading in Developing Countries". Capturing the Gains Working Paper No. 25. Manchester: University of Manchester.

Lee, Joonkoo, Gary Gereffi, and Sang-Hoon Lee. 2016. "Social Upgrading in Mobile Phone GVCs: Firm-Level Comparisons of Working Conditions and Labour Rights". In *Labour in Global Value Chains in Asia*, edited by Dev Nathan, Meenu Tewari and Sandip Sarkar, 315–352. Cambridge: Cambridge University Press.

Leschke, Janine, Andrew Watt, and Mairéad Finn. 2008. "Putting a Number on Job Quality? Constructing a European Job Quality Index". ETUI-REHS Working Paper No. 2008-03. Brussels: European Trade Union Institute for Research, Education and Health and Safety.

Lloyd, Caroline, and Susan James. 2008. "Too Much Pressure? Retailer Power and Occupational Health and Safety in the Food Processing Industry". *Work, Employment and Society* 22 (4): 713–730. https://doi.org/10.1177/0950017008098366.

Long, J. Scott, and Jeremy Freese. 2006. *Regression Models for Categorical Dependent Variables Using Stata*. 2nd ed. College Station, TX: Stata Press.

Lu, Yingying, and Yixiao Zhou. 2021. "A Review on the Economics of Artificial Intelligence". *Journal of Economic Surveys* 35 (4): 1045–1072. https://doi.org/10.1111/joes.12422.

Marcolin, Luca, Sébastien Miroudot, and Mariagrazia Squicciarini. 2016. "The Routine Content of Occupations: New Cross-Country Measures Based on PIAAC". OECD Trade Policy Papers, No. 188. Paris: OECD.

Milanez, Anna. 2023. "The Impact of AI on the Workplace: Evidence from OECD Case Studies of AI Implementation". OECD Social, Employment and Migration Working Papers, No. 289. Paris: OECD.

Milberg, William, and Deborah Winkler. 2011. “Economic and Social Upgrading in Global Production Networks: Problems of Theory and Measurement”. *International Labour Review* 150 (3–4): 341–365. https://doi.org/10.1111/j.1564-913X.2011.00120.x.

Nadvi, Khalid, John T. Thoburn, Bui Tat Thang, Nguyen Thi Thanh Ha, Nguyen Thi Hoa, Dao Hong Le, and Enrique Blanco De Armas. 2004. “Vietnam in the Global Garment and Textile Value Chain: Impacts on Firms and Workers”. *Journal of International Development* 16 (1): 111–123. https://doi.org/10.1002/jid.1066.

Nazareno, Luísa, and Daniel S. Schiff. 2021. “The Impact of Automation and Artificial Intelligence on Worker Well-Being”. *Technology in Society* 67 (November): 101679. https://doi.org/10.1016/j.techsoc.2021.101679.

Nikulin, Dagmara, Aleksandra Parteka, and Joanna Wolszczak-Derlacz. 2022. “Working Conditions in Europe: The Role of Global Value Chains and Advanced Digital Production-Driven Technological Specialisation”. ETUI Working Paper No. 2022.12. Brussels: European Trade Union Institute.

Nikulin, Dagmara, Joanna Wolszczak-Derlacz, and Aleksandra Parteka. 2022. “Working Conditions in Global Value Chains: Evidence for European Employees”. *Work, Employment and Society*, 36 (4): 701–721. https://doi.org/10.1177/0950017020986107.

OECD (Organisation for Economic Co-operation and Development). 2023. *OECD Employment Outlook 2023: Artificial Intelligence and the Labour Market*. Paris.

Papke, Leslie E., and Jeffrey M. Wooldridge. 1996. “Econometric Methods for Fractional Response Variables with an Application to 401(k) Plan Participation Rates”. *Journal of Applied Econometrics* 11 (6): 619–632. https://doi.org/10.1002/(SICI)1099-1255(199611)11:6<619::AID-JAE418>3.0.CO;2-1.

Parteka, Aleksandra, and Joanna Wolszczak-Derlacz. 2019. “Global Value Chains and Wages: Multi-Country Evidence from Linked Worker–Industry Data”. *Open Economies Review* 30 (3): 505–539. https://doi.org/10.1007/s11079-018-9518-8.

———. 2020. “Wage Response to Global Production Links: Evidence for Workers from 28 European Countries (2005–2014)”. *Review of World Economics* 156 (4): 769–801. https://doi.org/10.1007/s10290-020-00380-4.

Parteka, Aleksandra, Joanna Wolszczak-Derlacz, and Dagmara Nikulin. 2024. “How Digital Technology Affects Working Conditions in Globally Fragmented Production Chains: Evidence from Europe”. *Technological Forecasting and Social Change* 198 (January): Article No. 122998. https://doi.org/10.1016/j.techfore.2023.122998.

Piasna, Agnieszka. 2018. “Scheduled to Work Hard: The Relationship between Non-standard Working Hours and Work Intensity among European Workers (2005–2015)”. *Human Resource Management Journal* 28 (1): 167–181. https://doi.org/10.1111/1748-8583.12171.

Reinecke, Juliane, Jimmy Donaghey, Adrian Wilkinson, and Geoffrey Wood. 2018. “Global Supply Chains and Social Relations at Work: Brokering across Boundaries”. *Human Relations* 71 (4), 459–480. https://doi.org/10.1177/0018726718756497.

Rossi, Arianna. 2013. “Does Economic Upgrading Lead to Social Upgrading in Global Production Networks? Evidence from Morocco”. *World Development* 46 (June): 223–233. https://doi.org/10.1016/j.worlddev.2013.02.002.

Salanova, Marisa, Susana Llorens, and Mercedes Ventura. 2014. “Technostress: The Dark Side of Technologies”. In *The Impact of ICT on Quality of Working Life*, edited by Christian Korunka and Peter Hoonakker, 87–103. Dordrecht: Springer.

Shen, Leilei, and Peri Silva. 2018. “Value-Added Exports and US Local Labor Markets: Does China Really Matter?” *European Economic Review* 101 (January): 479–504. https://doi.org/10.1016/j.euroecorev.2017.10.009.

Smith, Adrian, and John Pickles. 2015. “Global Value Chains and Business Models in the Central and Eastern European Clothing Industry”. In *Foreign Investment in Eastern and Southern Europe after 2008: Still a Lever of Growth?*, edited by Béla Galgóczi, Jan Drahokoupil and Magdalena Bernaciak, 319–353. Brussels: ETUI.

Spitz-Oener, Alexandra. 2006. “Technical Change, Job Tasks, and Rising Educational Demands: Looking Outside the Wage Structure”. *Journal of Labor Economics* 24 (2): 235–270. https://doi.org/10.1086/499972.

Steffgen, Georges, Philipp E. Sischka, and Martha Fernandez de Henestrosa. 2020. “The Quality of Work Index and the Quality of Employment Index: A Multidimensional Approach of Job Quality and Its Links to Well-Being at Work”. *International Journal of Environmental Research and Public Health* 17 (21): 7771. https://doi.org/10.3390/ijerph17217771.

Sutherland, John. 2012. “Job Attribute Preferences: Who Prefers What?” *Employee Relations* 34 (2): 193–221. https://doi.org/10.1108/01425451211191896.

Tarafdar, Monideepa, Cary L. Cooper, and Jean-François Stich. 2019. “The Technostress Trifecta: Techno Eustress, Techno Distress and Design – Theoretical Directions and an Agenda for Research”. *Information Systems Journal* 29 (1): 6–42. https://doi.org/10.1111/isj.12169.

Timmer, Marcel P., Erik Dietzenbacher, Bart Los, Robert Stehrer, and Gaaitzen J. de Vries. 2015. “An Illustrated User Guide to the World Input–Output Database: The Case of Global Automotive Production”. *Review of International Economics* 23 (3): 575–605. https://doi.org/10.1111/roie.12178.

Timmer, Marcel P., Bart Los, Robert Stehrer, and Gaaitzen J. de Vries. 2016. “An Anatomy of the Global Trade Slowdown Based on the WIOD 2016 Release”, GGDC Research Memoranda No. 162. Groningen: University of Groningen.

Turja, Tuuli, Tuomo Särkikoski, Pertti Koistinen, Oxana Krutova, and Harri Melin. 2024. “Job Well Robotized! – Maintaining Task Diversity and Well-Being in Managing Technological Changes”. *European Management Journal* 42 (1): 67–75. https://doi.org/10.1016/j.emj.2022.08.002.

UNIDO (United Nations Industrial Development Organization). 2019. *Industrial Development Report 2020: Industrializing in the Digital Age*. Vienna.

van der Velde, Lucas. 2020. “Within Occupation Wage Dispersion and the Task Content of Jobs”. *Oxford Bulletin of Economics and Statistics* 82 (5): 1161–1197. https://doi.org/10.1111/obes.12368.

Visser, Jelle. 2019. *ICTWSS Database: Version 6.0*. Amsterdam: Amsterdam Institute for Advanced Labour Studies.

Wang, Zhi, Shang-Jin Wei, and Kunfu Zhu. 2013. “Quantifying International Production Sharing at the Bilateral and Sector Levels”. NBER Working Paper No. 19677. Cambridge, MA: National Bureau of Economic Research.

Webb, Michael. 2020. “The Impact of Artificial Intelligence on the Labor Market”. Working Paper available at SSRN. http://dx.doi.org/10.2139/ssrn.3482150.

Wooldridge, Jeffrey M. 2010. *Econometric Analysis of Cross Section and Panel Data*. 2nd ed. Cambridge, MA: MIT Press.

Appendix

Summary statistics of the variables used in estimations

Variables	*N*	Mean	Standard deviation	Min.	Max.
Hourly wage in US$ (SES)	9 526 268	16.75	14.40	1.25	111.34
Job quality indices (EWCS)					
Social environment	25 681	77.49	23.62	0.00	100.00
Skills and discretion	27 694	55.51	21.36	1.98	98.37
Physical environment	27 679	83.73	14.54	0.00	100.00
Work intensity	27 612	32.92	18.72	0.00	100.00
Prospects	27 598	63.02	19.74	0.00	100.00
Working time	27 694	70.92	13.95	7.97	100.00
Technological exposure (*Tech*)					
Software exposure	27 585	43.28	19.62	6.00	87.00
Robot exposure	27 585	46.71	23.33	10.00	86.00
AI exposure	27 585	44.01	20.11	11.00	90.00
AIOI	27 585	−0.02	0.87	−1.53	1.28
Individual, job and firm characteristics (EWCS)					
sex (0 for female, 1 for male)	27 689	0.48	0.50	0.00	1.00
ageyoung (binary variable for people below 30 years)	27 694	0.16	0.37	0.00	1.00
ageaverage (binary variable for people of age 30–49 years)	27 694	0.47	0.50	0.00	1.00
ageold (binary variable for people of age 50 years and more)	27 694	0.34	0.47	0.00	1.00
loweduc (low educational attainment level, ISCED-2011, levels 1–2)	27 576	0.18	0.38	0.00	1.00
mededuc (medium educational attainment level, ISCED-2011, levels 3–4)	27 576	0.49	0.50	0.00	1.00
higheduc (high educational attainment level, ISCED-2011, level 5+)	27 576	0.33	0.47	0.00	1.00
skill1 (skill level according to ISCO skill level)	27 585	0.11	0.31	0.00	1.00
skill2 (skill level according to ISCO skill level)	27 585	0.52	0.50	0.00	1.00
skill3 (skill level according to ISCO skill level)	27 585	0.12	0.32	0.00	1.00
skill4 (skill level according to ISCO skill level)	27 585	0.26	0.44	0.00	1.00
unlimited (1 for contract of unlimited duration, 0 for otherwise)	23 979	0.78	0.41	0.00	1.00
part-time (1 for part-time employment, 0 otherwise)	26 201	0.21	0.40	0.00	1.00

(*Cont.*)

Summary statistics of the variables used in estimations (*concl.*)

Variables	*N*	Mean	Standard deviation	Min.	Max.
Individual, job and firm characteristics (SES)					
sex (0 for female, 1 for male)	9 526 356	0.50	0.50	0.00	1.00
ageyoung (binary variable for people below 30 years)	9 526 356	0.17	0.38	0.00	1.00
ageaverage (binary variable for people of age 30–49 years)	9 526 356	0.52	0.50	0.00	1.00
ageold (binary variable for people of age 50 years and more)	9 526 356	0.31	0.46	0.00	1.00
loweduc (low educational attainment level, ISCED-2011, levels 1–2)	9 526 356	0.16	0.37	0.00	1.00
mededuc (medium educational attainment level, ISCED-2011, levels 3–4)	9 526 356	0.45	0.50	0.00	1.00
higheduc (high educational attainment level, ISCED-2011, levels 5+)	9 526 356	0.39	0.49	0.00	1.00
full-time (1 if full-time employment, 0 for part-time employment)	9 526 356	0.82	0.39	0.00	1.00
shortdur (length of employment in the company: less than one year)	9 526 356	0.13	0.34	0.00	1.00
meddur (length of employment in the company: 1 to 4 years)	9 526 356	0.30	0.46	0.00	1.00
longdur (length of employment in the company: 5 to 14 years)	9 526 356	0.37	0.48	0.00	1.00
vlongdur (length of employment in the company: 15 years and more)	9 526 356	0.20	0.40	0.00	1.00
public (1 for public, 0 for private companies)	9 242 482	0.37	0.48	0.00	1.00
GVC measures					
FVA/export (share of foreign value added in exports)	27 653	0.14	0.10	0.01	0.70
GII (Global Import Intensity)	27 694	0.25	0.18	0.00	0.99

Notes: For SES data, we use weighted statistics with weights based on the rescaled grossing-up factor for employees (from the SES), normalized by the number of observations per country. Job quality indices may range from 0 to 100 and cover the dimensions of social environment, skills and discretion, physical environment, work intensity, prospects and working time quality (see table SA3 in the supplementary online appendix).

Source: Our own compilation based on job quality indices from the 2015 EWCS, wages from the 2014 SES, technological exposure indicators from Webb (2020), AIOI (AI occupational impact) from Felten, Raj and Seamans (2019) and sectoral data from the 2016 WIOD.