Bargaining models, the quality of work and rent-sharing in the era of digitalisation

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Table of contents

Abstract

This paper studies how increasing digitalisation relates to the changing labour demand and the quality of the work. Using data for 18 industries from 14 European countries between 2006 and 2018, we explore whether the increased use of software is associated with job quality through a change in the incidence of atypical labour, measured as the shares of part-time and of fixed-term workers on total employment. We also investigate whether this association has been amplified or mitigated by the coordination of wage bargaining and by rent-sharing mechanisms established between workers and employees. Our findings reveal that industries with higher software usage tend to have lower rates of part-time work, especially in countries with stricter wage-setting regulations. Additionally, we observe that wage coordination strengthens the role of digitalisation on job quality. Conversely, the prevalence of fixed-term work does not seem to be related to digitalisation, but is lower in countries with a stronger wage coordination. Furthermore, our analysis shows that the role of wage coordination is independent of other labour market characteristics, such as centralised wage setting, trade union influence, employment protection laws, as well as other dimensions of the institutional setting (i.e., product market regulation). Overall, our results are robust to controlling for the role of the megatrends, namely general technological change, globalisation, environmental issues, and demographic trends.

1. Background

Welfare states rely on the creation of wealth through economic activity to improve the well-being of all citizens. Major trends, such as climate change, globalisation, demographic change, and digitalisation challenge this model, as they bring about costs and risks that are unequally distributed over the population. In the labour market, in particular, recent technological advancements have had varying impacts on employment and wages for different groups of workers (Anzolin, 2021). In European countries, computer use improved job quality as measured by work discretion and work intensity (Menon et al., 2020) while industrial robots reduced job quality in terms of work intensity (Antón et al., 2023) as well as meaningfulness and autonomy of work (Nikolova et al., 2024). The full extent of the impact of technological change on job quality, however, remains underexplored. Job quality refers to the impact that job characteristics have on workers' physical, mental and social well-being (Holman, 2013). These job characteristics involve working conditions (work environment, work organisation, etc.), employment conditions (working time, remuneration, training, career prospects, etc.), and social relations (support, say, formal worker representation, institutions, etc.). The quality of jobs thus affects workers' well-being as well as their ability to share the economic benefits of technological progress. In this paper, we study the effect of digitalisation, as measured by software use, on employment conditions, proxied by the incidence of temporary and part-time work. We also account for collective bargaining models which may moderate the relationship between technology adoption and labour market outcomes.

Since the onset of industrialisation, there have been four technological or industrial revolutions. The first industrial breakthrough revolved around steam engines, and the second around electric power and steel manufacturing. This 'first machine age' has enabled new ways of producing and new products, while replacing and speeding up physical tasks, leading to accelerating economic growth. The third revolution, introducing digital information and communication technology, has enhanced cognitive tasks and replaced some routine non-manual tasks. Finally, the ongoing fourth technological revolution is disconnecting technology from humans (i.e. AI, big data, machine learning) and may also augment and replace non-routine non-manual tasks requiring creativity (Ford, 2013).

An extensive strand of literature has discussed the degree to which technological change over time has affected the jobs distribution, i.e. leading to job polarisation up to some point (Autor, 2015; Goos et al., 2009). The question at hand, however, is how technology, beyond impacting labour demand or businesses, affects job quality. This depends on psychological and economic dynamics.

In the psychology of work, the job demand–control model has put forward the idea that job quality depends on the balance between what is demanded from a worker and the resources at her disposal to handle those demands (Bakker and Demerouti, 2007; Karasek, 1979). If workers have few demands and few resources, work is considered ‘passive’. If workers have few demands but many resources, the result is ‘low-strain work’. The combination of many demands and many resources leads to ‘active work’, and the combinations of many demands but few resources indicate ‘high-strain work’.

Technologies replacing physical tasks have to some extent decreased workloads, and work tools may give workers more control over the production process. However, industrialised production has also exposed workers to new or increased physical risks when handling machinery, and can lead to sentiments of alienation and estrangement, in particular in Tayloristic production settings (Previtali and Fagiani, 2015). Similarly, advances in digital information technology may also have both positive and negative effects on job quality. For instance, computerisation of work can be thought of as increasing job demands due to more complex work with higher skills requirements, or more intense work as computers outpace workers and integrate work processes to reduce slack or idle time (Biron and van Veldhoven, 2016; Riva et al., 2022). The increasing dependency on algorithms may further lead to decreasing job control as working time autonomy and task discretion could be taken away from workers and more flexibility is required on digital platforms. The fourth technological revolution may accelerate this trend as AI and platforms could even undermine the capacity of workers to organise around regulating working conditions (Davis, 2024). Note that while initially technology is often adopted as an aid to workers, the comparative advantage is lost when the technology becomes more widely adopted, hence the beneficial outcomes may be short-lived (Bartel and Lichtenberg, 1987). In sum, as work effort in itself can be thought of as a disutility to workers, technological change may bring additional disamenities and, on top of that, deregulate work. However, to the extent that workers are already well-organised or when extensive labour regulation is in place, the adoption of technology and its impact may vary (Gallie, 2007).

The economic pathway determining job quality, and employment conditions in particular, runs through the labour market. The impact of automation and digital technologies on the labour market has been extensively studied from various angles (see Dauch, 2018). In Europe, automation has led to a decrease in job separations, particularly in economies with lower labour costs (Bachmann et al., 2024). Similarly, evidence suggests that the use of artificial intelligence has resulted in faster employment growth in occupations that heavily rely on computers and are more exposed to this new technology (Georgieff and Hyee, 2021).

Innovation and technological advancements have influenced how workers benefit from economic rents (Van Reenen, 1996). Marginal productivity should increase when technology is adopted if it does not replace the job altogether. This means labour demand shifts up, and workers will be willing to supply more working hours for higher wages up (less part-time work) until workers have a sufficiently high income to meet their needs and prefer more leisure time instead of more labour income (backward sloping labour supply). The disamenities from worsening working conditions, as suggested above, can be thought of as lowering wages instead, in which supply falls back and wages would have to increase to motivate workers (Schokkaert et al., 2011). Finally, employers will typically engage more temporary workers when adjusting the workforce if output levels change, for instance because of the adoption of new technologies, but in the long run, with stable output levels, they should prefer employee retention to avoid hiring costs and losing experience. Unless technology is disruptive in terms of work organisation (e.g. platform work in the fourth technological revolution) or creates sudden large output gaps, the share of fixed-term contracts should eventually decrease in those activities that adopt the technology (Kalleberg, 2000). Taken together, however, the increasing efforts from changing working conditions and the increasing labour supply from higher wages, may offset each other. On the other hand, derived demand for work in other sectors, for instance in low-paid, low-skilled personal services in the context of job polarisation, may show a different (cross)-elasticity to technological changes (Autor and Dorn, 2013).

The extent to which workers are organised to reap the benefits of increasing productivity (rent-sharing) may influence the relation between technological change and job quality. Recent studies have shown that wages are becoming less responsive to rent creation (Bell et al., 2023), and economic rents are increasingly being accrued by top executives and workers at the upper end of the wage distribution (Kline et al., 2019). Regular workers in particular appropriate a larger share of rents in sectors with higher growth rates in total factor productivity, and investment in ICT (Fukao et al., 2022). Rent-sharing is, however, influenced by labour market regimes. In Japan, a higher proportion of the rents accrue to regular workers in industries with a lower share of non-regular contracts, stronger union density and in productions where the accumulation of knowledge occurs through experience and seniority. Conversely, in Germany, individual wages are less responsive to rents in industries with stronger union and in presence of industry-wide wage contracts (Guertzgen, 2009). In Belgium, in decentralised industries where contract conditions are renegotiated at company-level, firms and workers always share production rents. In contrast, centralised industries only see wages positively correlated with firm profits when there is a complementary collective agreement at the company level (Rusinek and Rycx, 2013). In Italy, female workers who switch from full-time to part-time contract regimes are found to earn more, likely due to the relatively higher protection accorded by unions and sectoral collective agreements (Devincienti et al., 2020).

There is a time-correlation and an interplay between technological change and other major trends. Research suggests that population ageing and subsequent labour shortages have driven the adoption of automation in industrial processes (Acemoglu and Restrepo, 2018; Abeliansky and Prettner, 2023). As the population ages, there is a growing demand for personal service and healthcare, sectors which typically employ more non-traditional workers and offer fewer opportunities for workers to negotiate better wages, due to a lower bargaining power of workers. Additionally, an ageing workforce leads to decreased job mobility, prompting companies to favour non-traditional contracts to maintain flexibility. This trend is likely to affect various sectors and could be particularly detrimental to younger workers (OECD, 2019).

Globalisation is another significant driving force behind the transformation of the labour market. Its deepening has been greatly facilitated by the widespread diffusion of new digital technologies and the rise of digital markets. Among the complex forces of globalisation, two stand out as particularly relevant for understanding job quality, job security, and opportunities for rent-sharing: global value chains and migration. The increasing international fragmentation of production and outsourcing practices has resulted in a significant increase in intermediate goods trade. This has led to intense competition among suppliers to reduce costs and ensure timely production. Consequently, local suppliers are under pressure to outsource and subcontract labour, often hiring workers for short periods of time on short-term contracts (Barriantes, 2013; ILO, 2016). On average, firms exposed to offshoring tend to have higher job separation, except for young workers and those with tertiary education (El-Sahli et al., 2022). Krentz et al. (2021) study the interplay between production fragmentation and technological change, finding evidence of reshoring in most OECD countries that is induced by automation. Reshoring is also found to be positively related to wages and employment for workers in professional occupations but not for workers with elementary-routine jobs. The impact of migration on job quality and worker gains is less clear, as natives and migrants cannot be often seen as substitute as they aim to respond to different types of labour demand (EIB, 2016).

Finally, the impact of climate change on employment has become a topic of increasing importance in both policy and academic circles (EC, 2014; ILO, 2018). Climate change has a range of effects on the labour market, with extremely hot weather reducing working hours and outdoor leisure (Graff Zivin and Neidell, 2014). Pollution has also been found to reduce worker productivity, both in jobs exposed to natural events such as agriculture (Graff Zivin and Neidell, 2012) and in jobs that are not, such as white-collar and service workers (Chang et al., 2019). However, adaptation policies to climate change, developed after the signing of the Kyoto Protocol, are believed to have significant positive effects on employment and working conditions. These policies can help to mitigate the negative effects of climate change on the labour market and create new opportunities for workers in emerging industries (EC, 2019).

Based on these premises, this paper aims at studying the effect of increasing digitalisation on the quality of work and how this depends on the model of wage of bargaining and rent sharing mechanisms established by firms and employees. Relying on data for 18 industries from 14 European countries between

2006 and 2018, we explore whether the increased use of software has affected job quality, measured as the share of part-time and of fixed-term workers in total employment. We develop a panel data regression analysis that exploits variation across countries in the wage bargaining models and across-industry variation in the propensity to invest in digital assets or to share the rents generated by production. In accomplishing this task, we address various econometric issues and, in particular, we control for the impact of the megatrends involving modern advanced economies, namely general technological change, globalisation, environmental issues, and demographic trends.

The remainder is organised as follows. Section 2 lays down the research questions of the work and illustrates the empirical strategy followed. Section 3 presents data whilst Section 4 provides some summary statistics. Section 5 displays econometric results. Finally, Section 6 concludes.

2. Research questions and empirical strategy

We investigate whether digitalisation in sectors is associated with change in labour demand and employment of atypical jobs, mainly part-time and temporary workers, and how this trend differs in relation to the wage bargaining model in force at the country level. We contend that the firm's decision to employ atypical workers is related to the mechanism of coordination of wage setting: this can be dispersed across firms and industries or, conversely, may be constrained by binding norms regarding maximum or minimum wage rates or wage increases, associated with centralised bargaining or unilateral government determination of wage schemes. This implies that the nature of wage coordination, along with other institutional characteristics that will be controlled for, could interplay with the labour market transformations driven by the main technological trajectories and other major economic and social trends, namely the megatrends described above.

We also look at whether the wage bargaining model is associated the workers' capacity to appropriate economic rents and, through this, influences the use of atypical jobs. Rent sharing is usually assumed to be proportional to the volume of profits in relation to the size of the value added to the production. As long as wage coordination enlarges the workforce capacity to gain rents from production, one might expect that countries in which wage coordination is strong and in industries where profit sharing is high, the proportion of atypical jobs is lower as workers may seek to hinder the use of atypical contract types which would reduce the base to gain further rents in the future. However, one cannot exclude that firms opt for this type of contracts to reduce the large bargaining power of insider workers.

We investigate whether digitalisation is related to the use of atypical jobs by carrying out a panel regression analysis utilising industry-level data for several European countries. Our main specification is defined as follows:

$$s_{ict} = \alpha_{ic} + \alpha_t + \alpha_1 \ln SW_{ict} + \alpha_2 WC_{ct} + \alpha_3 RS_{ict} + C_{(i)ct} + \mathcal{E}_{ict} \quad (1)$$

In Eq. (1), the dependent variable s is the share of atypical workers in total employment in industry i, country c, at time t. As discussed in the previous section, considerable attention in the literature has been devoted to examining the impact of digitalisation on the labour market. Early studies focused on the diffusion of computers and software, while more recent research has delved into robotisation and the widespread adoption of technologies driving the fourth industrial revolution, particularly AI systems, algorithms, and platforms. In this paper, we utilise a comprehensive measure of the digitalisation intensity of production, defined as the cumulative value of software investment (denoted by SW). Software investment has indeed played a crucial role in shaping the labour market over the past two decades, facilitating the creation of new digital assets in the latest years and serving as a key investment form in the intangibles' economy together with R&D (Haskel and Westlake, 2017). Furthermore, software investment is less susceptible to measurement challenges compared to emerging digital technologies like AI systems, which are often assessed based on the recruitment of computer scientists and AI experts. In our regression model, SW is expressed relative to employment and taken in logs.

In Eq. (1), WC is a country-level measure of the coordination of wage setting, with a higher score indicating more coordination. RS is a measure of the extent of the potential rent sharing established at the industry level between workers and entrepreneurs. We run this regression model with the Fixed Effect OLS estimator, including industry-by-country intercepts α_{ic} and year fixed effects α_t. This estimation procedure offers the advantage to exploit longitudinal variation in the data for identifying the association between digitalisation, wage coordination, and job quality, and in the meantime gain in efficiency exploiting variation over time of the variables.

In Eq. (1), the former set of dummies is aimed to collect all unobservable characteristics, specific to each industry-country pair, that do not change over time and that structurally affect the firms' propensity to rely on atypical work. The latter set of dummies captures, conversely, the effect of time shocks that shape the usage of atypical work across all industries. $\mathcal{E}_{ict}$ is a stochastic error term. In order to avoid omitted variable bias, the baseline specification also includes a set of control variables, C, that distinguishes megatrends and institutional factors. The megatrends include general technological change, globalisation, ageing, and environmental issues. The institutional factors include other important dimensions of the labour market, such as the enforcement of the employment protection legislation, etc., as well as the institutional setting of product markets that may indirectly affect labour demand, namely the knock-on effect of upstream market regulation (see below for a broader discussion).

We explore the moderating role of the wage coordination in shaping the linkage between digitalisation (and that of rent-sharing) and atypical jobs, by introducing an interaction term into the previous equation, as shown below:

$$s_{ict} = \alpha_{ic} + \alpha_t + \alpha_1 \ln SW_{ict} + \alpha_2 WC_{ct} + \alpha_3 RS_{ict} + \alpha_4 \ln SW_{ict} \times WC_{ct} + \cdots + \mathcal{E}_{ict} \quad (2)$$

The interaction term captures whether the strength of the association between digitalisation and the use of atypical contracts is amplified (α_1 and α_4 having the same sign) or mitigated (α_1 and α_4 having an opposite sign) by the bargaining model and, if at all, this effect shows up above or below a given threshold in the diffusion of the new technology. In all estimations above, the use of a proxy for rent-sharing is crucial to exclude that high levels of wage coordination transmit to labour demand for atypical work by raising the economic rents appropriated by workers. Conversely, the interaction between wage coordination and the rent-sharing variable is utilised for identifying whether the role of these two forces mutually reinforce. The latter interaction is omitted by Eq. (2) for simplicity of notation.

It is worth to discuss a few important points concerning our empirical strategy. The *first issue* concerns the economic interpretation of the estimated coefficients, which changes across regressors in relation to their different nature. Since our dependent variable is the share of employees with atypical contracts in the sector workforce, the coefficient of the digitalisation intensity can be seen as a semi-elasticity given that this explanatory variable is expressed in logs. It would imply that a parameter of 0.01 corresponds to the absolute increase in the dependent variable associated with a 100% in the digital intensity of production. In other words, a coefficient value of 0.01 would signify that doubling the stock of software per worker (namely a 100% increase in the main proxy for digitalisation) would expand the share of atypical jobs on total industry employment, for instance, from 0.10 to 0.11.

By contrast, given the discrete nature of the measure of wage coordination, the parameter of this regressor can be seen as unit impact, quantifying the absolute change in the dependent variable induced by a unit-increase in the value of the regressor (i.e., from 0 to 1, or from 1 to 2, and so on). For instance, a parameter of 0.01 for this explanatory variable would indicate that the share of atypical workers would pass, to say, from 0.45 to 0.46 as a consequence of a one-point (score) increase in wage coordination. Finally, the rent sharing potential (i.e. the profit rate) is expressed as share and hence the associated coefficient represents an elasticity. For instance, a parameter of 0.01 would indicate the percentage increase in the dependent variable and, to get the absolute change in the share of atypical jobs, one has to divide the estimated elasticity for the ratio between the average values of the explanatory and dependent variables.

Furthermore, it should be pointed out that, in Eq. (2), the overall impact of digitalisation depends on the degree of wage bargaining; it also implies that the overall impact of wage coordination changes along the distribution of the intensity of digitalisation. Specifically, the marginal effect of wage coordination is given by $\alpha_2 + \alpha_4 \ln SW_{ict}$ where α_2 identifies the direct (main) effect of the variable whilst $\alpha_4 \ln SW_{ict}$ quantifies the additional interaction effect. Below, we will quantify the marginal effect of wage coordination at the mean value of the conditioning variable (either digitalisation or rent-sharing) and plot the predicted values of former variable along the full distribution of the latter.

The *second issue* concerning our empirical strategy relates to the type of variation in the bargaining model we are able to capture with our empirical framework. Indeed, our specification is a pure panel fixed-effect model and hence results are immune to the bias associated with all unobservable, idiosyncratic characteristics of each industry-by-country pair that are correlated with the bargaining model. The impact of such unobservable, time-invariant factors may be confounded with that of the bargaining model as this dimension of the labour market changes slowly over time (if at all) and may affect labour demand at an industry level in relation to the nature of firm production. This risk is unlikely to be circumvented using a set of country and industry dummies, as such deterministic components force systematic idiosyncratic variation to change by country and type of production distinctly.

The *third issue* deals with estimation bias potentially induced by simultaneity feedbacks (reverse causality). We conservatively consider the estimated parameters as an association between the right-hand side variables and our proxies for job quality. However, it is unlikely that the usage of atypical contracts at the level of an individual industry can influence the wage bargaining model in the country; indeed, as discussed above, this dimension of the labour market has historically changed very slowly over time. Conversely, reverse causality is admittedly an issue for the identification of the impact of digitalisation (or also that of rent- sharing). To address this, we follow the strategy devised by Rajan and Zingales (1998) and Ciccone and Papaionannou (2023). In studying the interplay between wage bargaining and digital transformation, we consider cross-industry variation in the industry propensity to invest in software and databases as a structural characteristic that does not change over time and is common to all countries. This is assumed to shape the linkage between wage bargaining with atypical job at the level of the individual industry, and can be inferred looking at the industry degree of digitalisation for a benchmark country (not included in the regression analysis). This would make identification of the moderating effect of wage coordination (relatively) immune to reverse causality. The results of these regressions are reported in Tables 7 and 8, and indicate that the linkage between digitalisation, wage coordination and atypical job may be causal.

3. Data description

The analysis is carried out using data at the level of 18 industries for 14 European countries observed between 2006 and 2018. We use data for industries classified at the two-digit level of NACE Revision 2. These have been aggregated up so to have major groupings common to all the sources used. The list of countries and industries covered by our analysis can be found in Table 1.

The dataset has been compiled by merging different sources. The quality of jobs is measured in terms of the proportion of atypical work on industry employment, defined as ratio to total employees of workers with part-time or fixed-term contracts. This information is available at the level of representative samples of individual workers from the Structure of Earnings Survey (SES) provided by Eurostat. This survey is conducted across European workers at four-year intervals, and is now available for 2006, 2010, 2014 and 2018. Our main estimates use data points taken at these benchmark years. The SES offers rich information on contract and work conditions for each employee. This data has been aggregated up based on the industry code of the firm of employment of surveyed workers. We match SES data, reclassified at industry level according to the NACE Revision 2 categorisation, to different other sources of data.

Our key explanatory variables are the intensity of digitalisation, wage coordination and the extent of rent-sharing. EU KLEMS is used as a primary source for information on industry accounts (source: EU KLEMS & INTANProd - Release 2023). We measure the degree of digitalisation as the deepening of software investment in the production; it is gauged in terms of the stock of computer software and databases, expressed as a ratio to industry employment.

The degree of wage coordination quantifies the strictness of the norms binding the coordination of workers and employers (and their representatives) in wage negotiation. This variable is defined as a score in a scale ranging from 1 (no coordination) to 5 (max coordination). This measure is available at country level from OECD/AIAS ICTWSS database on 'Institutional Characteristics of Trade Unions, Wage Setting, State Intervention and Social Pacts'.

Rent sharing is measured as ratio of profits to value added, expressed at current prices. Profits are expressed as gross operating surplus and, since this information is unavailable from EU KLEMS, we use data from OECD STAN.

We use two main categories of control variables. The first includes a set of proxies for the megatrends described above, that may affect the use of atypical jobs, and whose impact may be confounded with that of our main explanatory variables if omitted from the regression. As a proxy for innovation effort, we use the stock of R&D expenditure (in constant prices 2015) expressed in ratio to employment. R&D is the second major category of intangible investments for several European countries. This variable is utilised to reflect industry differences in general trend in technological advances. As in Bournakis et al. (2018), we control for the effect of globalisation and the firm propensity to outsource production tasks abroad, building a measure of offshoring intensity, defined as the share of imported intermediate inputs in gross production, expressed at current prices. These variables are taken from OECD TiVA (Trade in Value Added) dataset. To account for environmental issues involved in production, we construct a measure of polluting intensity of the industry, defined in terms of the amount of CO2 emissions, expressed as ratio to employment. Labour demand and hence the use of atypical jobs may be affected by increasing constraints on polluting activities. Environmental norms usually force firms to undertake long-term investment towards green modes of production. This may require the hiring of specialised and high-qualified workers that firms seek to hold off by offering typical contracts. Information on CO2 is available on a yearly base at industry-by-country level (source: OECD Trade in Embodied CO2 Database, TECO2). This measure is derived by exploiting detailed information on tons of emissions associated with the production of different categories of products. The amount of pollution for each industry-country pair is then computed considering the domestic final demand of the product and thar part induced by international trade associated (namely, caused by foreign demand). We derive a measure of workforce ageing employed at the sectoral level and consider the share of employee with more than 50 years of age. This is derived from Labour Account sheets included in the latest version of EU KLEMS. These data have been originally assembled from various versions of the Labour Force Survey and are available at the one-digit level of the NACE Rev. 2 classification. It implies that the manufacturing sector is considered as a whole. Furthermore, we use a measure of labour productivity, namely real value added (in constant price) per worker to control for labour efficiency. Labour productivity is quite stagnant in several European countries, and this may influence firms' decision of hiring and the type of contracts offered.

The sensitivity analysis (in the Appendix) considers a larger control set, including different proxies for the current wave of digitalisation. Specifically, we use data on AI patenting (per worker), available at the country level, to control for the shift of the economy towards the new generation of disruptive technologies (source: OECD Patent database). We also consider more in depth the extent of automation of production processes and use as regressor the installed stock of industrial robots at industry level (source: IFR). Finally, we include more general measures of capital investment to account for complementary and substitutability between different type of labour and capital assets. If omitted, these factors may be mis-interpreted as the effect of software use on atypical jobs.

Table 1. Country and industry coverage

	Country	Obs.		NACE Rev. 2	Obs.
BE	Belgium	67	B_D_E	Mining and quarrying; Electricity, gas, steam and air-conditioning supply; Water supply, sewerage, waste management and remediation	53
CZ	Czech Republic	71	C10-C15	Food products, beverages and tobacco products; Textiles, apparel, leather and related products	42
DE	Germany	36	C16-C18	Wood and paper products, and printing	42
EE	Estonia	40	C19-20_C22	Coke, and refined petroleum products; Chemicals and chemical products; Rubber and plastics products,	37
ES	Spain	71	C21_C26-27_C33	Pharmaceuticals, medicinal chemical and botanical products; Computer, electronic and optical products; Electrical equip.; Repair and installation of machinery	41
FR	France	71	C23	Other non-metallic mineral products	27
HU	Hungary	40	C24-C25	Basic metals; Fabricated metal products	39
IT	Italy	70	C28	Machinery and equipment n.e.c	37
LT	Lithuania	40	C29-C32	Transport equip.; Other manufacturing	39
LV	Latvia	62	F	Construction	54
NL	Nether-lands	70	G	Wholesale and retail trad	54
SE	Sweden	71	H	Transportation and storage	54
SK	Slovakia	71	I	Accommodation and food service activities	54
UK	United Kingdom	54	J-N	Publishing; Telecommunications; IT and other information services; Financial and insurance activities; Real estate activities; Legal, accounting; Scientific research and development; Other professional, scientific and technical activities; Administrative and support service activities	53
			O	Public administration and defence, compulsory social security	48
			P	Education	54
			Q	Human health services; Residential care and social work active.	53
			R-S	Arts, entertainment and recreation; Other services	53
	Total	**834**	**Total**		**834**

The group of institutional controls include proxies for the centralisation of wage bargaining (source: OECD AIAS), the trade union density (source: OECD AIAS), the employment protection legislation, EPL (source: OECD EPL indicators) and upstream product market regulation, PMR (source: OECD Regulation Impact). As for our measure of wage coordination, the centralisation of wage bargaining is defined at country level, as a score ranging between 0.875 (no centralisation) to 5 (max centralisation). This indicator combines different dimensions of the bargaining model, namely the predominant level at which the wage bargaining takes place, the incidence of additional enterprise bargaining, the existence of wage setting in sectoral agreements and other opening clauses in sectoral collective agreements. Trade union density is defined as share of employees who are member of a trade union in the economy. This variable should capture the strength of the bargaining power of the workforce, a factor related but distinct from the nature of the bargaining model. As a measure of EPL we consider the strictness of the rules for the dismissals of regular contract workers. The propensity to fire is a structural characteristic that changes across industries.[1] Therefore, following Lewandowski et al. (2023), we get this information from a benchmark country, namely the UK, and multiply it with the national based score of Employment Protection Legislation, that varies between 0 (min strictness) and 5 (max strictness). The propensity to fire is computed as mean value of the redundancy rate per industry (number of job separations over total employment) from 2009 and 2019. In estimates using this variable, the benchmark countries is left out from the analysis. Our index of EPL on regular contract is then normalised so to range between 0 and 1.

The index of upstream regulation is developed by OECD to measure the effect of regulation in (upstream) services on downstream activities. This is constructed as a score associated with the strictness of regulation in network service industries, weighted by the intensity of purchases of intermediate inputs from the regulated industries to the downstream industries, as expressed as ratio of total intermediate purchases. The propensity to buy inputs upstream is a structural characteristic, depending on the technology of production. This is usually inferred looking at a benchmark country not included in the regression to mitigate reverse causality issues. In this respect, the OECD Regulation Impact database includes a version of the data built using weights that reflect inter-industry (Input-Output) intermediate input transactions for the US, taken at a pre-sample year (2005). The upstream PMR indicator is rescaled so to range from 0 and 1.

Finally, all monetary variables expressed in levels are in Power Purchasing Parity (PPP) for the US dollars (2015 constant prices) and taken in logs. We use US dollars as numeraire as the United States, albeit not included in the analysis, are used as a reference (benchmark) to measure systematic technology differences existing across industries. Details on data sources and methods of construction of the variables can be found in Table 2.

[1] In a related study of the same WeLaR work-package, Lewandowski et al. (2023) study how EPL and PMR shape the relationship between automation technologies and occupation opportunities of different demographic groups in Europe, identified on the basis age, gender, and education.

Table 2. List of variables: data sources and method of construction

Definition	Method of computation	Level	Source
Dependent vars.			
Part-time contracts	Part-time workers / Total employees, where Total employees is given by the sum between part-time and full-time employees	Industry-by-country	EU-SES
Fixed-term contracts	Employees with temporary or fixed duration contract / Total employees, where Total employees is given by the sum of employees with Indefinite duration, temporary-fixed duration and apprenticeship contracts	Industry-by-country	EU-SES
Main regressors			
Software stock per worker	Stock of Computer Software and Database /Total employment	Industry-by-country	EU KLEMS
Coordination of wage-setting	1 = Fragmented wage bargaining; 2 = Some coordination of wage setting; 3 = Procedural negotiation guidelines; 4 = Non-binding norms and/or guidelines; 5 = Binding norms	Country	OECD/AIAS ICTWSS
Rent-sharing	Gross Operating Surplus / Value added (both in current prices)	Industry-by-country	OECD STAN
Megatrend Controls			
R&D stock per worker	Stock of R&D expenses / Total employment	Industry-by-country	EU KLEMS
Offshoring intensity	Gross imports of intermediate products / Gross production	Industry-by-country	OECD TiVA
C02 emission per worker	Emissions embodied in international trade and final domestic demand / Total employment	Industry-by-country	OECD, Trade in Embodied CO2 Database (TECO2)/ EU KLEMS
Employees aged 50 and more	Employees with 50 years and more / Total employment	Industry-by-country	EU KLEMS
Institutional controls			
Centralised collective bargaining	Central = Level - (rAEB*2+WSSA+OCG)/8), where Level: The predominant level at which wage bargaining takes place (in terms of coverage of employees);rAEB: Reach or incidence of additional enterprise bargaining; WSSA: Wage setting in sectoral agreements; OCG: Opening clauses in sectoral collective agreements	Country	OECD/AIAS ICTWSS
Trade Union density	Employees who are member of a trade union / Total employees	Country	OECD/AIAS ICTWSS
Employment Protection Legislation (EPL)	Employment Protection Legislation on dismissals of regular contract workers (country level) multiplied by industry firing rate (UK benchmark, avg 2009-18)	Industry-by-country	OECD EPL indicators
Product Market Regulation (PMR)	Service industry regulation (country level) multiplied by the industry propensity to purchase service intermediate inputs (US benchmark, 2005)	Industry-by-country	OECD Regulation Impact

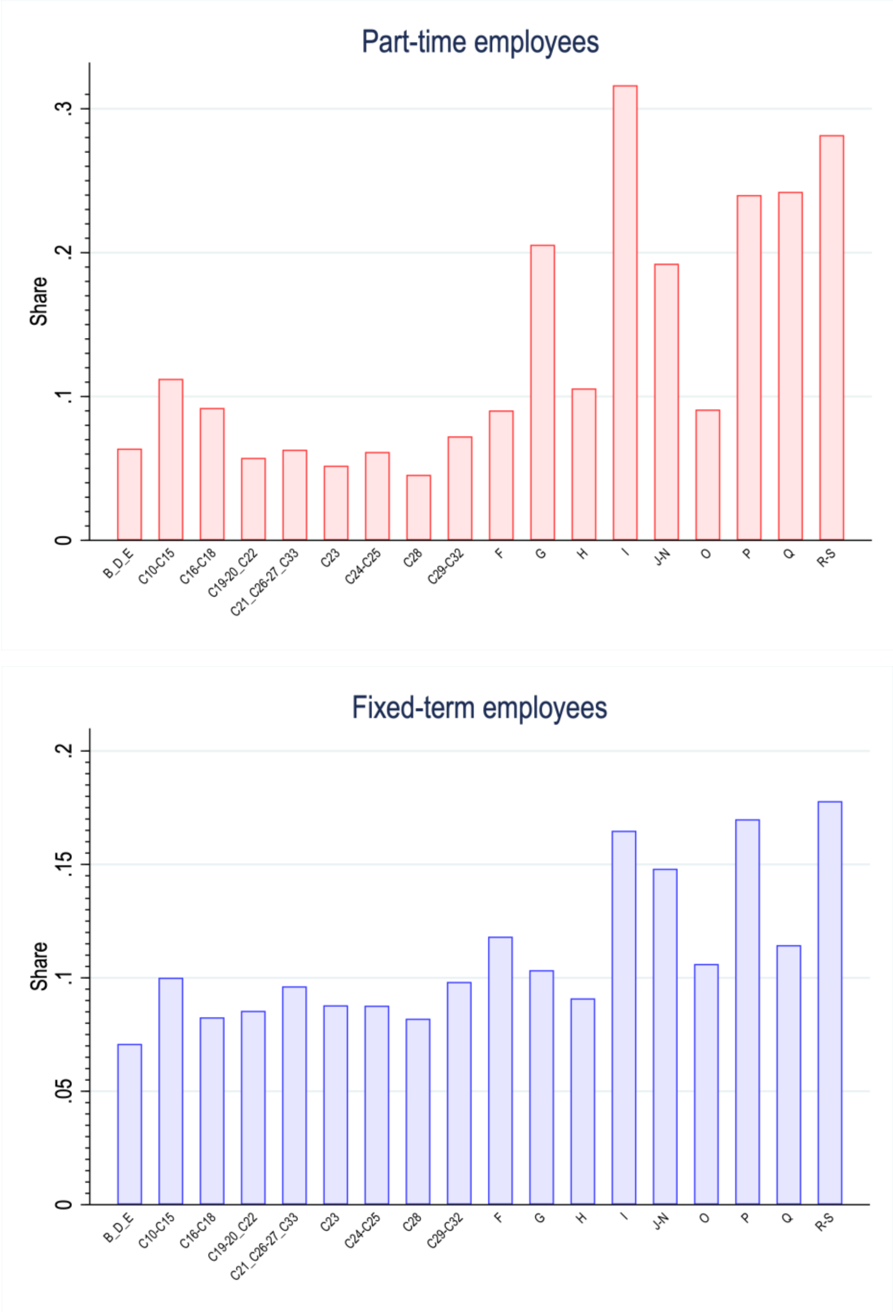
4. Summary statistics

Table 3 provides key summary statistics for the main variables used in the regression analysis. The share of part-time workers on total employment is 0.15, whilst that of fixed-term contract workers is slightly lower (0.10). The distribution of part-time workers is relatively more skewed, showing a standard deviation as large as the mean value, whilst the median value is relatively low.

When we look at our main explanatory variables, there emerges a wide variation across industries in the software intensity of production, namely the stock of software capital per worker in USD (mean: 1.346; median: 0.003) compared to wage coordination's score (mean: 2.55; median: 2) and rent sharing potential or profit share (mean: 0.408; median: 0.409). An uneven distribution can be also found for some economic controls where the average largely exceeds the median, such as R&D stock per worker (mean: 1.32; median: 0.003) and labour productivity (mean: 44.5; median: 0.050). The share of workers aged 50 years and more amounts to 55% of the workforce, although this seems to be increasing rapidly. Intermediate inputs purchased abroad (offshoring intensity) corresponds to a share of 0.14 on industry gross output. On average, each industry produces 0.4 tons of C02 per each employee annually. If we look institutional factors variation is smaller than economic controls, given that most reflect common variation at country level. The mean value of the EPL index is 0.390 (median 0.392), and 0.039 (median 0.015) for upstream indicator of PMR; on average, the degree of centralisation of wage bargaining is 2.04 whilst the share of trade union members on total employees is 0.24.

A greater detail on cross-industry differences can be captured by Figure 1, which reports the mean of our main variables for each industry. The largest share of part-time workers can be found for Accommodation and food service activities (category I, NACE Rev. 2) where almost one-third of employees is part-timer. Arts, entertainment and recreation; Other services (category R-S) stands out for the largest share of workers with temporary contract (0.178). The highest digitalisation intensity is found for publishing, telecom and professional services (category J-N), where the stock of software and database per worker amounts to 6 thousand dollars. Mining and quarrying; Electricity, gas, steam and air-conditioning supply (cat. B_D_E) and Construction (cat. F) denote the highest level of wage coordination (2.665). The former of these industries also presents the highest profit share on value added (0.636).

Figure 1. Mean statistics by industry (Panel A)



B_D_E: Mining and quarrying; Electricity, gas, steam and air-conditioning supply; Water supply, sewerage, waste management and remediation; **C10-C15:** Food products, beverages and tobacco products; Textiles, apparel, leather and related products; **C16-C18:** Wood and paper products, and printing; **C19-20_C22:** Coke, and refined petroleum products; Chemicals and chemical products; Rubber and plastics products; **C21_C26-27_C33:** Pharmaceuticals, medicinal chemical and botanical products; Computer, electronic and optical products; Electrical equip.; Repair and installation of machinery; **C23:** Other non-metallic mineral products; **C24-C25:** Basic metals; Fabricated metal products; **C28:** Machinery and equipment n.e.c; **C29-C32:** Transport equip.; Other manufacturing; **F:** Construction; **G:** Wholesale and retail trade; **H:** Transportation and storage; **I:** Accommodation and food service activities; **J-N:** Publishing; Telecommunications; IT and other information services; Financial and insurance activities; Real estate activities; Legal, accounting; Scientific research and development; Other professional, scientific and technical activities; Administrative and support service activities; O: Public administration and defence, compulsory social security; **P:** Education; **Q:** Human health services; Residential care and social work activities; **R-S:** Arts, entertainment and recreation; Other services

Figure 1. Mean statistics by industry (Panel B)

B_D_E: Mining and quarrying; Electricity, gas, steam and air-conditioning supply; Water supply, sewerage, waste management and remediation; **C10-C15:** Food products, beverages and tobacco products; Textiles, apparel, leather and related products; **C16-C18:** Wood and paper products, and printing; **C19-20_C22:** Coke, and refined petroleum products; Chemicals and chemical products; Rubber and plastics products; **C21_C26-27_C33:** Pharmaceuticals, medicinal chemical and botanical products; Computer, electronic and optical products; Electrical equip.; Repair and installation of machinery; **C23:** Other non-metallic mineral products; **C24-C25:** Basic metals; Fabricated metal products; **C28:** Machinery and equipment n.e.c; **C29-C32:** Transport equip.; Other manufacturing; **F:** Construction; **G:** Wholesale and retail trade; **H:** Transportation and storage; **I:** Accommodation and food service activities; **J-N:** Publishing; Telecommunications; IT and other information services; Financial and insurance activities; Real estate activities; Legal, accounting; Scientific research and development; Other professional, scientific and technical activities; Administrative and support service activities; **O:** Public administration and defence, compulsory social security; **P:** Education; **Q:** Human health services; Residential care and social work activities; **R-S:** Arts, entertainment and recreation; Other services

Table 3. Summary statistics: all sample (unweighted statistics)

Variable	Unit	Mean	Median	Standard	Variable	Unit
Dep. variables						
Part-time contracts	Share (0-1)	0.151	0.094	0.148	0.001	0.819
Fixed-term contracts	Share (0-1)	0.104	0.081	0.095	0.000	0.761
Explanatory variables						
Software capital per worker	2015 USD PPP (1,000)	1.353	0.002	9.221	0.000	122.3
Wage coordination	Scale (1-5)	2.546	2.000	1.317	1.000	5.000
Rent sharing	Share (0-1)	0.408	0.411	0.150	0.037	0.852
Economic controls						
R&D stock per worker	2015 USD PPP (1,000)	1.335	0.003	11.37	0.000	181.7
Offshoring intensity	Share (0-1)	0.142	0.102	0.188	0.000	2.202
CO2 emissions per worker	Emission (tons)	0.040	0.003	0.113	0.000	0.946
Aged employees (>=50 yrs)	Share (0-1)	0.557	0.359	0.335	0.137	1.000
Labour productivity	2015 USD PPP (1,000)	44.74	0.050	210.8	0.004	1811
Institutional controls						
Employment Protection Legislation	Scale (0.875-5)	0.390	0.392	0.205	0.000	0.962
Product Market Regulation	Share (0-1)	0.039	0.015	0.078	0.001	0.578
Centralised collective barg.	Scale (0-1)	2.043	2.250	0.910	0.875	4.875
Trade Union density	Scale (0-1)	0.239	0.177	0.175	0.044	0.723

5. Econometric results

5.1. Baseline regressions

We start the empirical analysis showing a set of baseline regressions in which our job quality variables are regressed against the main explanatory variables using alternative deterministic components (Table 4). Estimates on the left-hand side of the table use the share of part-time employees as dependent variable, whilst the right-hand side considers the share of workers with fixed-term contracts. In each group, the first regression uses a true fixed-effect model based on industry-by-country (pair) fixed effects, along with time dummies. The second regression admits two different groups of dummies to capture distinctly variation that change across countries and across industries. These two regressions are firstly run on data for the benchmark years (2006, 2010, 2014 and 2018). Then, they are replicated using annual data both for the dependent variables and for the regressors, where the values for job quality variables are linearly interpolated at intermediate years. The rationale of the latter regressions is to get more precise estimates by having the possibility to exploit variation in the explanatory variable at a higher frequency.

Table 4. Baseline regressions

Dependent variable	(1) Share of part-time employees	(2)	(3)	(4)	(5) Share of fixed-term employees	(6)	(7)	(8)
Explanatory variables:								
Software stock p.w.	-0.015***	-0.005	-0.017***	-0.005**	0.003	-0.011***	0.002	-0.005**
(log)	(0.005)	(0.004)	(0.003)	(0.002)	(0.006)	(0.004)	(0.003)	(0.002)
Wage coordination	-0.025***	-0.025***	-0.012***	-0.013**	-0.024***	-0.022***	-0.006**	-0.013**
(scale)	(0.005)	(0.009)	(0.003)	(0.006)	(0.006)	(0.008)	(0.003)	(0.006)
Rent-sharing	-0.034	-0.003	-0.004	0.003	-0.017	-0.015	0.018	0.003
(share)	(0.032)	(0.031)	(0.016)	(0.016)	(0.038)	(0.026)	(0.017)	(0.016)
Years	Benchmark	Benchmark	All	All	Benchmark	Benchmark	All	All
Ind.-by-country FE	Yes	No	Yes	No	Yes	No	Yes	No
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes
Country FE	No	Yes	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	834	838	2,730	2,734	834	838	2,730	2,734
R-squared	0.037	0.010	0.023	0.004	0.018	0.020	0.002	0.004

Notes: FE-OLS regressions with standard errors clustered by industry and countries in parentheses. All explanatory variables are one-year lagged with respect to the dependent variable. ***, **, * significant at 1, 5, 10% level.

Estimates on the left-hand side of Table 4 reveal that the share of part-time workers is higher in sectors where the intensity of digitalisation is low and in countries where wage coordination is modest. Conversely, rent-sharing mechanisms do not seem to play any role in explaining the systematic differences across sectors in this dimension of job quality. This pattern of results holds irrespective of the set of determinants and the frequency of the data. Using data at benchmark years produces greater parameter estimates for wage coordination, as this tends to vary very slowly over time (if at all). Using data at annual frequency yields more efficient estimates for digitalisation. Note that the parameter size of the latter variable is down-stated (in absolute terms) when we use country and industry fixed separately (columns (2) and (4)).

According to our benchmark estimates in column (1), a sector with the stock of software per worker twice as large as the average would have a share of part-timers 0.015 lower with respect to the mean value of 0.15 (namely 0.135). The coefficient of wage coordination is slightly larger as each unit-point difference in the value of this explanatory variable would translate into a 0.025 lower share of part-timers (0.125 with respect to the mean of 0.150).

The results for the share of fixed-term contracts, shown on the right-hand side of the table (see columns (5) to (8)), somewhat differ from the previous one as wage coordination is the only variable that is consistently related to this dimension of job quality. This implies that a unit-point increase in wage coordination is associated with a -0.024 lower share of part-timers (0.086 with respect to the mean). This result is broadly confirmed even if we control for the share of part-time workers in the regression in column (5), so to exclude that the impact of wage coordination ends to capture the effect on the other dimension of job quality. In other words, we can exclude the risk that when the shares of part-time and fixed-term contract workers move together, the significance of wage coordination in the equation for the share of fixed-term contracts may be driven by the association of the explanatory with the other dimension of job quality (e.g., the share of part-time workers). Similarly, estimates in column (1) do not change even when including the share of fixed-term employees. These robustness checks are not reported in regressions tables for the sake of brevity. These, however, also illustrate that there is complementarity in the use of atypical contracts, as the share of part-timers is higher in industries with a higher share of fixed-term contracts (and vice-versa).

5.2. Robustness to megatrends and other drivers of atypical work

The results of the sensitivity analysis conducted in our benchmark estimates are shown in Table 5 for the share of part-time employees, and Table 6 for the share of workers with fixed-term contracts. In each group of regressions, we first introduce some economic controls, and then a set of institutional factors, that may confound the effect of digitalisation and wage coordination found above. Our main results on the drivers of atypical jobs are largely robust to such robustness checks.

Some interesting findings emerge, nonetheless, from Tables 5 and 6. First, the proportion of workers with part-time contracts is lower in industries with a high offshoring intensity and a greater labour productivity. The former effect is quantitatively important and may signal that firms rely upon this category of workers to implement marginal or low value-added tasks, i.e., those activities that can be easily outsourced abroad. This suggests that part-timer labour and off-shored intermediates could be regarded as substitutes. The negative coefficient of value added per worker may instead reveal that the incidence of part-timers on total workforce is lower where labour input is more efficient and productive. This may reflect the capacity of workers to act as insiders and exploit non-monetary mechanisms of rent-sharing to hinder the expansion of atypical job, as these contracts reduce their bargaining power. For sake of rigour, we cannot exclude that causation runs from the dependent variable to labour productivity, implying that valued added per worker would be higher in sectors with a lower proportion of part-time workers. There is also indication that the share of part-time workers is higher in sectors with an older workforce (see Column (5), Table 5), this finding is not robust to the inclusion of other controls, as shown by estimates in Column (7).[2]

[2] In Table A.2 of the Appendix we report the results of additional robustness checks conducted controlling for a larger array of technological factors, namely, the stock of installed industrial robots (source: IFR), the counts of total, ICT, AI and Green patent applications at EPO (source: OECD Patent statistics), all expressed in per worker terms. The share of part-time jobs is found to be negatively and significantly related to robotisation, innovation (patenting) in the field of ICT and Green technologies.

Table 5. Robustness to control factors (share of part-time employees)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variable	Share of part-time employees								
Explanatory variables:									
Software stock p.w. (log)	-0.015***	-0.012**	-0.014***	-0.015***	-0.016***	-0.015***	-0.014***	-0.014**	-0.016**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.007)	(0.007)
Wage coordination (scale)	-0.025***	-0.024***	-0.025***	-0.024***	-0.025***	-0.024***	-0.024***	-0.023***	-0.015***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
Rent-sharing (share)	-0.034	-0.025	-0.040	-0.028	-0.038	-0.015	-0.027	-0.024	-0.035
	(0.032)	(0.032)	(0.032)	(0.033)	(0.032)	(0.034)	(0.034)	(0.037)	(0.038)
Megatrends									
R&D stock p.w. (log)		0.000							
		(0.003)							
Offshoring (share)			-0.088***				-0.088***	-0.077	-0.089*
			(0.030)				(0.030)	(0.053)	(0.053)
CO2 emissions p.w. (log)				-0.009					
				(0.007)					
Workers aged 50 & more (share)					0.024*		0.022		
					(0.013)		(0.013)		
Value added per worker						-0.023**	-0.020*	-0.039***	-0.036***
						(0.011)	(0.011)	(0.012)	(0.012)
Institutional controls									
EPL (scale)								0.267***	0.305***
								(0.055)	(0.056)
PMR (scale)								0.275**	0.422***
								(0.115)	(0.149)
Centralised collective bargaining (scale)									-0.008*
									(0.004)
Union density (share)									0.101
									(0.076)
Years	Bench-mark	Bench-mark	Bench-mark	Bench-mark	Bench-mark	Bench-mark	Bench-mark	Bench-mark	Bench-mark
Industry-by-country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	834	815	834	834	834	834	834	722	682
R-squared	0.037	0.034	0.047	0.039	0.041	0.042	0.055	0.105	0.122

Notes: FE-OLS regressions with standard errors clustered by industry and countries in parentheses. All explanatory variables are one-year lagged with respect to the dependent variable. All regressions are run on benchmark years (2006, 2010, 2014, 2018). ***, **, * significant at 1, 5, 10% level.

Table 6. Robustness to control factors (share of fixed-term employees)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variable	Share of fixed-term employees								
Explanatory variables:									
Software stock p.w. (log)	0.003	0.006	0.003	0.004	0.002	0.003	0.006	0.009	-0.004
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.009)	(0.008)
Wage coordination (scale)	-0.024***	-0.024***	-0.024***	-0.023***	-0.024***	-0.023***	-0.024***	-0.023***	-0.042***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
Rent-sharing (share)	-0.017	-0.011	-0.019	-0.008	-0.023	-0.000	-0.011	-0.050	-0.035
	(0.038)	(0.037)	(0.038)	(0.038)	(0.038)	(0.039)	(0.038)	(0.045)	(0.041)
Megatrends									
R&D stock p.w. (log)		-0.009***					-0.009***	-0.012***	-0.005*
		(0.003)					(0.003)	(0.004)	(0.003)
Offshoring (share)			-0.032						
			(0.035)						
CO_2 emissions p.w. (log)				-0.014*			-0.007		
				(0.008)			(0.008)		
Workers aged 50 & more (share)					0.030*		0.031**	0.027	0.028*
					(0.015)		(0.015)	(0.017)	(0.016)
Value added per worker						-0.021			
						(0.013)			
Institutional controls									
EPL (scale)								0.184	0.213
								(0.150)	(0.179)
PMR (scale)								0.096	0.030
								(0.072)	(0.065)
Centralised collective bargaining (scale)									0.015***
									(0.005)
Union density (share)									-0.450***
									(0.088)
Years	Benchmark	Benchmark	Benchmark	Benchmark	Benchmark	Benchmark	Benchmark	Benchmark	Benchmark
Industry-by-country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	834	815	834	834	834	834	815	707	671
R-squared	0.018	0.027	0.018	0.021	0.022	0.021	0.034	0.046	0.094

Notes: FE-OLS regressions with standard errors clustered by industry and countries in parentheses. All explanatory variables are one-year lagged with respect to the dependent variable. All regressions are run on benchmark years (2006, 2010, 2014, 2018). ***, **, * significant at 1, 5, 10% level.

Some further valuable insights arise when we extend the array of institutional factors that may affect atypical jobs. The centralisation of wage setting and the bargaining power of the workforce, as proxied by the rate of trade union membership, do not show any significant association with the share of part timers. These findings lend strong support to the hypothesis that the nature of the norms on wage setting, and how they are enforced, matter for the demand for this type of atypical jobs. This argument is supported even when we control for the strictness of regulation on firing of permanent workers. Since the parameter of this regressor corresponds to an elasticity, the absolute change in the share of part-timers (i.e., the marginal effect of EPL) is obtained by multiplying the estimated coefficient with the ratio between the means of explanatory and the dependent variable (namely, 0.390 and 0.151). This yields a value of 0.11 which signals that this type of atypical jobs is very responsive to the enforcement of EPL. It should also be pointed out that a similar results with product market regulation. The share of part-timers is higher in industries more exposed to regulated service inputs' providers with higher regulation (and hence mark-up). Due to such knock-on effects on the use of service intermediates, downstream industries are likely to look for greater flexibility through the use of atypical labour.

Robustness checks for the share of employees with fixed-term contracts in Table 5 largely support our baseline estimates. Among economic controls, there emerges a robust negative effect of the intensity of R&D investment. In other words, in more innovative industries the incidence of this type of atypical job is lower probably as R&D-doing firms seek to preserve their competitive advantage by keeping in-house key competence and offering permanent jobs. This is higher in sectors where innovation is derivative and relies on firm-specific human capital accumulation (Griffith and Macartney 2014). Innovative firms are also found to pay higher wages, proportionally more to low-skilled workers (Aghion et al. 2019). Consistently with this pattern, a larger share of income accrues to labour in industries that invest intensively more in R&D (O'Mahony et al. 2021).[3]

Again, even for the share of employees with fixed-term contracts, there is evidence that industries with on older workforce have a higher proportion of atypical job. This finding appears statistically more robust than found for the share of part-time workers in Table 5. Interestingly, the last two regressions of Table 6 reveal that the regulation of the labour and product market do not exert any effect on the firm propensity to offer temporary contracts. However, a significant role is played by the centralisation of wage setting and union membership. Contrary to wage coordination, the former seems to promote the incidence of fixed-term contracts, whilst in countries where unions are numerically stronger this type of atypical job is significantly lower. The marginal effect of the latter factor is quantitatively important as corresponds to a change in the share of fixed-term contracts of -0.19 (=-0.450 × (0.239/0.104)).

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[3] As the results in Table A.3 illustrate, the results for the share of fixed-term contracts are robust to controlling for innovation achievements in different technological fields and to the intensity of robotisation. The share of fixed-term contracts is found to be negatively and significantly related to general patenting, but positively to the patenting in the fields of AI.

5.3. The moderating role of wage coordination

In the last part of the paper, we investigate whether wage coordination mediates the impact of digitalisation and rent sharing and helps explain cross-industry differences in the proportion of atypical jobs.

The results of this exercise are shown in Table 7 for the share of part-time work. Column (2) introduces the interaction between software stock per worker (in logs) and wage coordination used in the benchmark regression (column (1)). This estimation reveals that the main association of digitalisation, as the coefficient of this explanatory variable taken alone is insignificant. However, this factor is negatively and significantly related to the share of part-time jobs when its effect is mediated by wage coordination. Put it in other words, industries rely less upon this form of atypical work in countries where wage coordination is stronger. As shown by the plot on the marginal effects of wage coordination at different percentiles of the distribution of software intensity (see Figure 2), the moderating role of wage coordination increases with the degree of the digitalisation and is statistically significant only in the second half of the distribution, i.e., for those sectors with a software intensity greater than the median of the sample.

To understand in what respect our parameter estimates are plagued by reverse causality, and if they can be interpreted as association or causal effects, in column (3) we use the industry intensity of software investment in a pre-sample period (i.e. between 1995 and 2005) for the United States and interact this variable with the country-specific measure of wage coordination. This should minimise the risk that our estimates are plagued by reverse causality, as software investment may change in response to a greater (lower) incidence of atypical jobs on industry workforce. Namely, firms may decide to invest more in software in those sectors where the labour quality is higher (i.e., with relatively fewer part-time workers). Note that, in column (3), to identify the main effect of the former variable, which does not change over time and is common to all countries, we leave industry fixed effects out from the regression but include country fixed effects; this would avoid that wage coordination captures the effect of some other institutional characteristic of the country which is hard to measure.

Estimates in column (3) confirm the mediating role of wage coordination, as shown by the parameter size of the interaction variable which lines up to the values of column (2). Three further insightful findings emerge from this regression. First, software stock per worker of the benchmark unit (the US) is found with a negative and significant effect, confirming that the propensity to invest in digital assets is a structural characteristic that shapes the firm's decision to offer or not atypical contracts. Second, the extent of rent sharing potential in European industries is negatively and significantly related to the share of part-timers. Therefore, the lack of significance of this variable in our earlier regression might indicate that its effects overlap with that of the intensity of software investment. Put differently, firms may invest relatively more in software where the profit share is higher (and vice-versa). Third, the coefficient size of the interaction variable is consistent with column (2). These findings remain unchanged even when we exclude country fixed effects from the regression (column (4)) or exclude the main effects of wage coordination and software stock per worker (column (5)). At this point, it should be emphasised that the latter regression is fully consistent with the difference-in-difference model of Rajan and Zingales (1998). It highlights that the effect found for our measure of digitalisation is robust to endogeneity issues and that wage coordination genuinely exacerbates the industry propensity to minimise the use of atypical contracts when investing in software.

In columns (6)-(7) of Table 7, we assess more in depth the impact of rent sharing potential and how it interplays with wage coordination. In column (6), we interact these two variables, using the value of each specific country. In column (7), we use the intensity of rent sharing potential for the benchmark country (the UK). These estimates exclude any type of mediating effect of wage coordination.

In the latter two columns, we expand the regression in column (6) introducing our proxies for EPL and PMR (main effect) and their interaction with wage coordination (indirect effect). Whilst column (9) does not offer clear insights on whether wage coordination shapes the impact of product market regulation, the results in column (8) unambiguously indicate that wage coordination mitigates the main effect of EPL.[4]

As a last step, we estimate the moderating effect of wage coordination on the share of fixed-term contrasts (see Table 8). The results of these regressions differ in some respect from those obtained for part-time workers. The parameter of wage coordination is stably negative and significant across specifications, ranging from -0.022 (column (8)) to -0.111 (column (2)).[5] This is slightly larger than the effect found for this explanatory variable in Table 7.A. Apparently, wage coordination has also a negative impact when interacted with software stock per worker; this would contrast the positive (direct) effect of digitalisation on this type of atypical jobs (column (2)). However, admittedly, the result for the moderating effect of wage coordination on the share of fixed-term contracts is not robust across specifications, especially in those using the propensity to software investment of the benchmark country (column (3)-(5)). Even in

[4] Figure A.1 reports the graphs for the marginal effect of wage coordination along the distribution of EPL both for the share of part-time and fixed-term contracts.

[5] Wage coordination turns out be insignificant in column (7) probably as this regression is over-specified by the interaction between this dimension of the bargaining model and rent sharing. Indeed, none of these variables, either when taken solely or when interacted, is found to be significant.

this group of regressions, rent sharing potential has a quite volatile coefficient and is often not significant. From the last two columns, it emerges that wage coordination interplays only with PMR, out-weighting only in part the effect of the latter variable.

Table 7. Moderating factors (share of part-time employees)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variable					Share of part-time employees				
Explanatory variables									
Software stock per worker (log)	-0.015***	-0.008							
	(0.005)	(0.006)							
Wage coordination (scale)	-0.025***	-0.063***	-0.081***	-0.033*		-0.017	-0.003	0.014	-0.024*
	(0.005)	(0.020)	(0.019)	(0.018)		(0.015)	(0.015)	(0.013)	(0.014)
Rent-sharing (share)	-0.034	-0.029	-0.075***	-0.089***	-0.145***	-0.024			
	(0.032)	(0.032)	(0.024)	(0.029)	(0.031)	(0.051)			
Moderating factors									
Software stock p.w. × Wage coordination		-0.005**							
		(0.003)							
Software stock p.w. (benchmark US, log)			-0.026***	-0.028***		-0.046***	-0.044***	-0.043***	-0.044***
			(0.006)	(0.007)		(0.003)	(0.003)	(0.002)	(0.003)
Software stock p.w. (US) × Wage coordination			-0.008***	-0.008***	-0.004***				
			(0.002)	(0.003)	(0.000)				
Rent-sharing × Wage coordination						-0.022			
						(0.018)			
Rent-sharing (benchmark UK)							0.064	0.029	-0.144***
							(0.060)	(0.029)	(0.031)
Rent-sharing (benchm. UK) × Wage coordination							-0.067***		
							(0.021)		
EPL								0.003	
								(0.038)	
EPL × Wage coordination								-0.092***	
								(0.012)	
PMR									-0.064
									(0.096)
PMR × Wage coordination									-0.048
									(0.033)
Industry-by-country FE	Yes	Yes	No	No	No	No	No	No	No
Industry FE	No	No	No	No	No	No	No	No	No
Country FE	No	No	Yes	No	No	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	834	834	834	834	834	834	780	763	722
R-squared	0.037	0.042	0.305	0.244	0.133	0.292	0.293	0.476	0.309

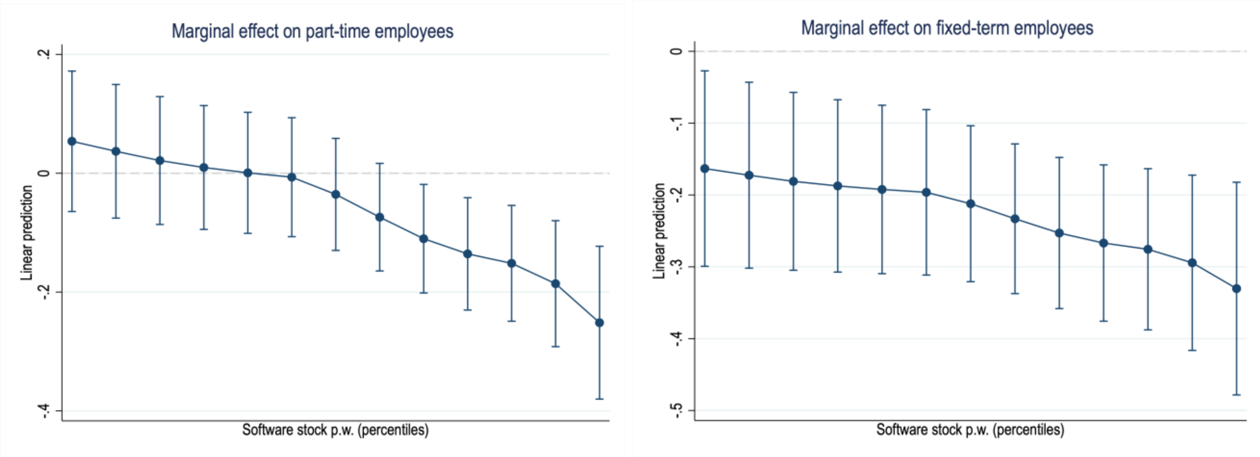
Notes: FE-OLS regressions with standard errors clustered by industry and countries in parentheses. All explanatory variables are one-year lagged with respect to the dependent variable. All regressions are run on benchmark years (2006, 2010, 2014, 2018). The benchmark value for the per-worker stock of software capital is computed as time-mean of US industries in the pre-sample period 1995-2005. The benchmark value for the rent-sharing (profit ratio) is computed as time-mean of UK industries in the pre-sample period 1995-2005. Regressions in column (7)-/(8) exclude the UK. ***, **, * significant at 1, 5, 10% level.

Table 8. Moderating factors (share of fixed-term employees)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variable					Share of fixed-term employees				
Explanatory variables									
Software stock per worker (log)	0.003	0.019***							
	(0.006)	(0.007)							
Wage coordination (scale)	-0.024***	-0.111***	-0.038***	-0.026**		-0.029***	-0.015	-0.022**	-0.026***
	(0.006)	(0.023)	(0.013)	(0.013)		(0.011)	(0.011)	(0.011)	(0.010)
Rent-sharing (share)	-0.017	-0.006	-0.053***	0.063***	0.043**	-0.083**			
	(0.038)	(0.037)	(0.018)	(0.021)	(0.021)	(0.037)			
Moderating factors									
Software stock p.w. × Wage coordination		-0.012***							
		(0.003)							
Software stock p.w. (benchmark US)			-0.006	-0.005		-0.012***	-0.012***	-0.012***	-0.012***
			(0.004)	(0.005)		(0.002)	(0.002)	(0.002)	(0.002)
Software stock p.w. (US) × Wage coordination			-0.002	-0.003*	-0.000				
			(0.001)	(0.002)	(0.000)				
Rent-sharing × Wage coordination						0.012			
						(0.013)			
Rent-sharing (benchmark UK)							0.008	-0.009	-0.077***
							(0.045)	(0.024)	(0.023)
Rent-sharing (benchm. UK) × Wage coordination							-0.023		
							(0.016)		
EPL								-0.069**	
								(0.031)	
EPL × Wage coordination								-0.005	
								(0.010)	
PMR									-0.257***
									(0.070)
PMR × Wage coordination									0.061**
									(0.024)
Industry-by-country FE	Yes	Yes	No	No	No	No	No	No	No
Industry FE	No	No	No	No	No	No	No	No	No
Country FE	No	No	Yes	No	No	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	834	834	834	834	834	834	780	763	722
R-squared	0.018	0.036	0.072	0.041	0.005	0.070	0.066	0.108	0.092

Notes: FE-OLS regressions with standard errors clustered by industry and countries in parentheses. All explanatory variables are one-year lagged with respect to the dependent variable. All regressions are run on benchmark years (2006, 2010, 2014, 2018). The benchmark value for the per-worker stock of software capital is computed as time-mean of US industries in the pre-sample period 1995-2005. The benchmark value for the rent-sharing (profit ratio) is computed as time-mean of UK industries in the pre-sample period 1995-2005. Regressions in column (7)-(8) exclude the UK. ***, **, * significant at 1, 5, 10% level.

Figure 2. Marginal effects of wage coordination on job quality measures and interplay with digitalisation



Notes: Marginal effect of wage coordination on the share of part-time (left-hand side panel) and fixed-term contracts (right-hand side panel) along the distribution of software per worker (in logs). The marginal effect is computed as $\alpha_2 + \alpha_4 \ln SW_{ict}$, where α_2 is the main effect of wage coordination and α_4 is the indirect impact of this variable which is channelled by the software stock per worker. The plot on the left-hand side is based on column (4), Table 7, the plot on the right-hand side is based on column (4) of Table 8.

6. Summary and concluding remarks

In this paper, we have studied the effect of digitalisation on the quality of the work with respect to employment conditions, measured by the share of part-time and of fixed-term workers in total employment. We found that part-time work is lower in industries with a more intensive use of software and in countries with binding norms on wage setting. Moreover, we have documented that wage coordination seems to reinforce the effect of digitalisation in limiting the use of part-time works. Conversely, the incidence of fixed-term work is not found to be affected by digitalisation, whilst it is lower in countries with stronger wage coordination. These findings are robust to controlling for the impact of the megatrends (technological change, ageing, climate change). Finally, the impact of wage coordination does not overlap with other important labour market characteristics, such as the degree of centralisation of wage setting, union power, the enforcement of employment protection legislation, or with other dimensions of the institutional setting (i.e., product market regulation). We conclude that in the digital age, wage coordination matters to improve working conditions, but that digitalisation does not necessarily adversely affect all aspects of job quality.

The study has some conceptual and methodological limitations. Firstly, different technologies affect work and workers in a different way, and future technologies may still perform differently. As the descriptive statistics have shown, software stock is concentrated in a limited number of sectors, whereas other sectors may invest more in other technologies such as robotisation and automation, with different outcomes. Similarly, job quality is a complex latent concept that includes working conditions, employment conditions and social relations. While the subset of particularly bad job quality on all dimensions must be shrinking when employment conditions improve as digitalisation intensifies, other aspects of work may be adversely affected and the precise pathways between the different components of job quality have not yet been fully explored and should inspire future research. Secondly, the analyses focused on industry-level outcomes, but had to rely on country-level data on collective bargaining. In addition, the variation over time in this data is limited, so that most studies focus on cross-sectional relations. Also, because of the industry-level structure, average effects were reported, whereas individual variation in the outcomes (e.g. by gender, age, or origins) may exist. Instead, future research could search for more longitudinal data, including the recent post-COVID period, when available, could distinguish short-run and long-run effects, and could set up a multi-level analytical structure to explore both cross-country and individual variation.

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Appendix

Table A1. Summary statistics: average values by industry

		B_D_E	C24-C25	I
Part-time contracts	Share	0.064	0.061	0.316
Fixed-term contracts	Share	0.071	0.088	0.165
Software capital per worker	US dollars	2.814	0.034	0.103
Wage coordination	Scale 1-5	2.665	2.645	2.644
Rent sharing	Share	0.636	0.348	0.415
		C10-C15	C28	J-N
Part-time contracts	Share	0.112	0.046	0.192
Fixed-term contracts	Share	0.100	0.082	0.148
Software capital per worker	US dollars	0.020	0.036	6.175
Wage coordination	Scale 1-5	2.645	2.656	2.644
Rent sharing	Share	0.424	0.360	0.485
		C16-C18	C29-C32	O
Part-time contracts	Share	0.092	0.072	0.091
Fixed-term contracts	Share	0.083	0.098	0.106
Software capital per worker	US dollars	0.026	0.052	1.696
Wage coordination	Scale 1-5	2.645	2.645	2.633
Rent sharing	Share	0.404	0.403	0.275
		C19-20_C22	F	P
Part-time contracts	Share	0.057	0.090	0.240
Fixed-term contracts	Share	0.085	0.118	0.170
Software capital per worker	US dollars	0.027	0.217	0.446
Wage coordination	Scale 1-5	2.645	2.665	2.621
Rent sharing	Share	0.487	0.440	0.159
		C21_C26-27_C33	G	Q
Part-time contracts	Share	0.063	0.205	0.242
Fixed-term contracts	Share	0.096	0.103	0.114
Software capital per worker	US dollars	0.093	0.859	0.208
Wage coordination	Scale 1-5	2.645	2.644	2.633
Rent sharing	Share	0.479	0.454	0.230
		C23	H	R-S
Part-time contracts	Share	0.052	0.106	0.282
Fixed-term contracts	Share	0.088	0.091	0.178
Software capital per worker	US dollars	0.021	1.219	0.634
Wage coordination	Scale 1-5	2.638	2.644	2.647
Rent sharing	Share	0.408	0.435	0.421

Table A2. Robustness checks to alternative measures of digitalisation and innovation (Share of part-time jobs)

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. variable			**Share of part-time employees**			
Explanatory variables:						
Software stock p.w. (log)	-0.015***	-0.015***	-0.015***	-0.014***	-0.015***	-0.015***
	(0.005)	(0.0052)	(0.005)	(0.005)	(0.005)	(0.005)
Wage coordination (scale)	-0.025***	-0.025***	-0.025***	-0.025***	-0.025***	-0.026***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Rent-sharing (share)	-0.034	-0.037	-0.034	-0.013	-0.033	-0.022
	(0.032)	(0.032)	(0.033)	(0.032)	(0.033)	(0.033)
Other technological factors						
Robot stock p.w. (log)		-0.013***				
		(0.004)				
Robot stock p.w. (log)		-0.013***				
		(0.004)				
Total patents p.w. (log)			0.006			
			(0.011)			
ICT patents p.w. (log)				-0.060***		
				(0.011)		
AI patents p.w. (log)					-0.011	
					(0.026)	
Green patents p.w. (log)						-0.032**
						(0.013)
Ind.-by-country FE	Yes	No	Yes	No	Yes	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	834	834	834	834	834	834
R-squared	0.037	0.049	0.038	0.073	0.038	0.045

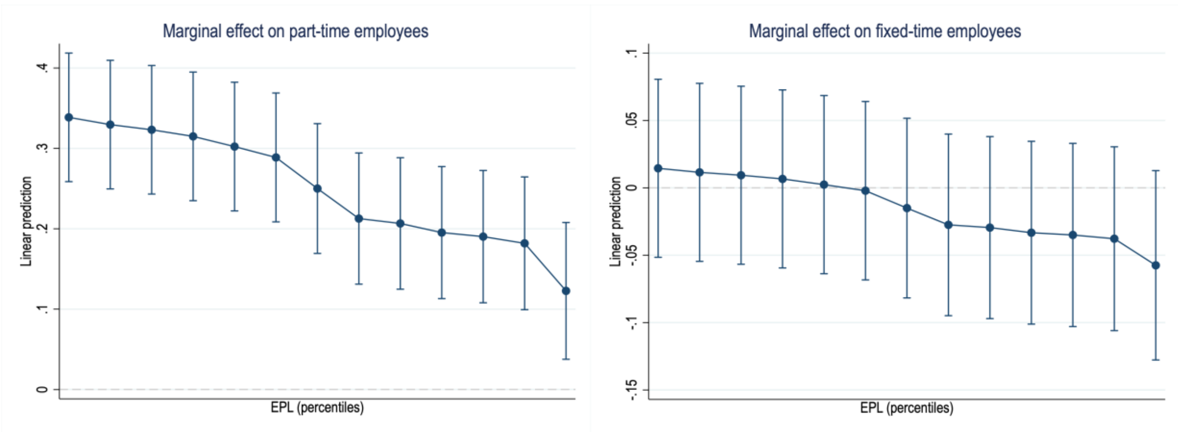
Notes: FE-OLS regressions with standard errors clustered by industry and countries in parentheses. All explanatory variables are one-year lagged with respect to the dependent variable. ***, **, * significant at 1, 5, 10% level.

Table A3. Robustness checks to alternative measures of digitalisation and innovation (Share of fixed-term jobs)

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. variable	**Share of fixed-term employees**					
Explanatory variables:						
Software stock p.w. (log)	0.003	0.003	0.004	0.003	0.001	0.003
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Wage coordination (scale)	-0.024***	-0.024***	-0.023***	-0.024***	-0.022***	-0.025***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Rent-sharing (share)	-0.017	-0.019	-0.004	-0.011	-0.028	-0.008
	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)
Other technological factors						
Robot stock p.w. (log)		-0.007				
		(0.005)				
Total patents p.w. (log)			-0.028**			
			(0.013)			
ICT patents p.w. (log)				-0.018		
				(0.013)		
AI patents p.w. (log)					0.065**	
					(0.030)	
Green patents p.w. (log)						-0.024
						(0.015)
Ind.-by-country FE	Yes	No	Yes	No	Yes	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	834	834	834	834	834	834
R-squared	0.018	0.020	0.023	0.020	0.023	0.021

Notes: OLS regressions with standard errors clustered by industry and countries in parentheses. All explanatory variables are one-year lagged with respect to the dependent variable. ***, **, * significant at 1, 5, 10% level.

Figure 3. Marginal effects of wage coordination on job quality measures and interplay with digitalisation



Notes: Marginal effect of wage coordination on the share of part-time (left-hand side panel) and fixed-term contracts (right-hand side panel) along the distribution of software per worker (in logs). The marginal effect is computed as $\alpha_2 + \alpha_4\ EPL_{ict}$, where α_2 is the main effect of wage coordination and α_4 is the indirect impact of this variable which is channelled by EPL. The plot on the left-hand side is based on column (8), Table 7, the plot on the right-hand side is based on column (8) of Table 8.

List of Tables

List of Figures

WeLaR is Horizon Europe research project examining the impact of digitalisation, globalisation, climate change and demographic shifts on labour markets and welfare states in Europe. It aims to improve the understanding of the individual and combined effects of these trends and to develop policy proposals fostering economic growth that is distributed fairly across society and generates opportunities for all.

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