Digital technologies, employment, and skills

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Abstract

This article investigates the relationship between the diffusion of digital technologies, employment, and skills. The empirical analysis is carried out on industry-level data of six major European economies (Germany, France, Spain, Italy, the Netherlands, and the UK) over the 2009–2014 period. We analyze two dimensions of digitalization: industries' consumption of intermediate inputs from digitally intensive sectors and investment in Information and Communication Technology (ICT) tangible and intangible assets, considering also patterns of demand, education, technological change, and offshoring. The results show that job creation in industries is positively associated with an increasing share of digital goods and services in total intermediate inputs and is negatively linked with processes of ICT capital deepening. We then explore how these two different patterns of digitalization are related to the evolution of four occupational groups—managers, clerks, craft, and Manual workers, defined on the basis of International Standard Classification of Occupations classes—finding a positive link between ICT consumption and managerial jobs, and negative ones between digital variables and mid-skill occupations.

JEL classification: J23, J24, J21, O3

1. Introduction

Digital technologies are reshaping modern economies. They can be understood as part of the current technological paradigm based on Information and Communication Technologies (ICTs), which is unfolding in the same way of previous technological revolutions associated with long-term cycles of growth (Freeman and Louçã, 2001). The diffusion of digital technologies throughout the economy is deeply changing the structure of advanced economies, the organization of production, the employment dynamics, and the skill composition of labor.

The emphasis on digitalization has opened the way to studies that tried to conceptualize and define such a phenomenon, measuring it with various indicators at the country, industry, and firm levels. Recent works (McKinsey Global Institute, 2015; Calvino *et al.*, 2018) represent an important step ahead in the direction of analyzing the multifaceted nature of digital technologies and their diffusion across industries. Nevertheless, in several studies, digitalization is assumed to be an undifferentiated phenomenon, with uniform effects on economic performance and employment; this approach is parallel to the way technological innovation has long been treated by mainstream economic studies, as a generic driver of progress.

This contribution moves from the assumption that both technological change and digitalization can develop along different trajectories, resulting from the firm- and industry-specific strategies, with possible contrasting outcomes on employment. An extensive literature has shown the importance to distinguish strategies of technological competitiveness, relying on product innovations, with employment-friendly outcomes, as opposed to strategies of cost competitiveness, relying on labor-replacing new processes (Pianta, 2000, 2001, 2005; Bogliacino and Pianta, 2010; Bogliacino *et al.*, 2013).

Building on the recent work by Calvino *et al.* (2018), we identify two different patterns of digitalization at the industry level, with potentially diverging economic effects. On the one hand, digitalization can spread mainly through industries' consumption of intermediate inputs from digital-intensive sectors; this reflects the diffusion of inputs based on ICT goods and services that have the potential to improve the performance of other industries, being incorporated in product innovations and contributing to higher-quality products and services. This dimension of digitalization may integrate a strategy of technological competitiveness and is expected to support the expansion of output and employment. On the other hand, digitalization can rely on industries' investment in tangible and intangible ICT assets, when computers, telecommunication networks, software, etc. become a key part of the capital stock used for production. However, the digital investment may be used in restructuring strategies, in particular when industries' demand stagnates—in a search for greater cost-competitiveness—contributing to job losses.

Industries are an important level of study for understanding the digital transformation, as they are characterized by specific technological opportunities and trajectories, by their position in inter-industry and international flows of goods and services (Dosi, 1982; Breschi *et al.*, 2000). Moreover, changes in employment at the industry level are jointly shaped by the evolution of technologies and demand patterns, allowing a more comprehensive assessment of the consequences on jobs (Pasinetti, 1981).

The empirical analysis of this contribution is carried out using the Sectoral Innovation Database (SID), covering 41 manufacturing and service industries for six major European countries (Germany, France, Spain, Italy, the Netherlands, and the UK) focusing on the years 2009–2014—the period after the financial crisis of 2008—when the recovery of European economies offers a relevant opportunity to investigate the role of digital technologies. Our data allow us to study two key dimensions of digitalization processes while controlling for a rich set of industry-level variables including information on innovation, economic performance, offshoring, as well as employment variables, broken down by occupations.

We first investigate how the diffusion of digital technologies is associated with total employment and then how it relates to changes in demand for four occupational groups—managers, clerks, craft, and manual workers. As shown in previous works (Bramucci *et al.*, 2017; Cirillo, 2017; Cirillo *et al.*, 2018), a focus on occupational groups allows to move beyond the high skilled vs. low skilled dichotomy (white-collar vs. blue-collar) and better reflects the hierarchy of occupations in terms of wage differences, levels of education, diversity of competences, and the task content of jobs. We report evidence on the growing polarization of the skill structure in European industries, with job creation concentrated at the top (the category of managers, professionals, and technicians) and at the bottom (the category of manual workers) of occupational groups (see Figures A2 and A3 in the Appendix).

The paper is structured as follows. The next section locates our contribution within the existing empirical literature dealing with the digitalization–employment nexus. Section 3 describes the dataset and the variables used in the empirical analysis and provides descriptive evidence. Section 4 presents the model and the econometric strategy adopted. The final section discusses the results of our study.

2. Digitalization and the future of jobs

The employment–digitalization nexus is at the center of a lively debate and is becoming a topic of policy concern. It is widely acknowledged that the diffusion of digital technologies throughout the economy is deeply changing the structure of advanced economies, the organization of production activities, the dynamics of employment, and the demand for skills. The literature dealing with the employment effects of digitalization and automation is however far from delivering a consensual view on current trends and future scenarios. Many contributions are impressionistic in nature and either emphasize the opportunities associated with digitalization or foresee bleak long-term effects. In particular, Frey and Osborne (2017) estimated that within the next 10–20 years, 47%

of jobs could be automated in the USA. The 2019 Employment Outlook of the Organisation for Economic Co-operation and Development (hereafter OECD) states that "technological progress offers new employment opportunities and that a significant risk of high technological unemployment is unlikely"; at the same time, it warns that "without immediate policy action, disparities among workers may rise and social cleavages may deepen between those who gain and those who lose from the ongoing changes in the world of work" (OECD, 2019). In this line are the findings of Arntz *et al.* (2016), who argue that 9% of jobs in OECD countries are susceptible to be replaced by machines, while Nedelkoska and Quintini (2018) estimate that about 14% of jobs in the OECD countries participating in the OECD Survey of Adult Skills (PIAAC) are highly "automatable," with a large variance across countries in the possibilities of automation.

Broader insights on the possibility of technological unemployment have come from Brynjolfsson and McAfee (2014), while many recent works have focused on the impact of robots. Graetz and Michaels (2018) did not find a significant negative impact of the number of robots on Europe's employment. Acemoglu and Restrepo (2017) assume robots to be competitors with workers and find significant negative effects on employment and wages. A survey on these issues is in Balliester and Elsheikhi (2018).

Further efforts have recently been made to provide a better understanding and measurement of the process of digitalization. In most studies, digitalization is conceived as the mere acquisition or use of single specific ICT items (computers, software, Internet and robots).[1] Results are consequently highly dependent on the type of ICT indicator taken into account. Important evidence has been produced by Eurostat's "Community survey on ICT usage and e-commerce in enterprises," covering the last 15 years, collecting data on a broad range of ICT-related activities carried out by firms and households, although with strong limitations in coverage and access to disaggregated data.

Other studies have tried to develop "all-in-one" ICT composite indicators (Guerrieri and Bentivegna, 2011; McKinsey, 2015; Calvino *et al.*, 2018), using some of the above sources. Calvino *et al.* (2018) have proposed a taxonomy of sectors combining data on ICT tangible and intangible (i.e., software) investment, the purchases of intermediate ICT goods and services, the stock of robots, the number of ICT specialists, and the share of turnover from online sales and also presenting an overall composite indicator of digitalization that synthesizes the main ICT dimensions taken into account. The study shows the existence of high sectoral heterogeneity of digital patterns and the presence of large cross-country differences within the same industries in the level of digitalization.

While studies of this type may be informative in highlighting general digital trends, the impact of digitalization has to consider how technology is used for different innovative strategies that may have complex effects on the quantity and quality of jobs.

Within the mainstream, studies have mainly followed *the skill-biased technological* change (SBTC) approach, followed in the most recent years by the so-called *routine-biased technological change* (RBTC) view. According to SBTC, the effect of technological change on employment is seen as the result of a race between labor and technology and associated with the increasing possibility of substituting low-skilled labor with ICT devices and systems; furthermore, it is assumed that digital technologies have differentiated effects on the productivity of labor depending on the skill content and the level of qualification of the labor force. New technologies are assumed to be complementary to high skill jobs (mostly due to the importance of cognitive skills related to the use of computers and IT devices) and are expected to penalize medium- and low-skilled jobs

1 Autor *et al.* (2003, 2013) and Michaels *et al.* (2014) take into account the role of investment in computer and IT capital; Graetz and Michaels (2018) and Dauth *et al.* (2017) assess the employment effects of the use of robots. Marcolin *et al.* (2016) use as ICT intensity indicator the proportion of workers employed in the business functions "ICT services" and "Engineering and related technical services" in a given industry, over the industry total. Data on a broader set of ICT-related technologies (including Internet, intranet, broadband, home pages, services offered via home pages, electronic commerce, and electronic data interchange) are used by a study of Böckerman *et al.* (2019). Evidence on the broad economic impact of digital technologies is in Evangelista *et al.* (2014). Data on robots are based on IFR (2018). Balsmeier and Woerter (2019) find that investment in digitalization supports the expansion of high-skilled employment and a decrease in demand for middle-skilled and low-skilled workers; the effects are driven by firms that use machine-based digital technologies (i.e., robots, three-dimensional printing, and Internet of Things), in contrast with firms that rely on non-machine digital technologies (enterprise resource planning, e-commerce, and social media) where no significant relation emerges.

due to a lower complementarity. This is in turn due to the fact that skilled (i.e., more educated) workers are more able to learn how to use new technologies and more flexible in the event of changing job assignment (Berman *et al.*, 1994; Autor *et al.*, 1998; Acemoglu, 2002; Acemoglu and Autor, 2011; Arvanitis and Loukis, 2015). This approach was deemed to be able to explain the long-term changes in the composition of employment observed in most industrialized countries from the early 1980s onward and, in particular, of the increasing share of the high-skill component of the workforce.

The skill-bias interpretation has then been challenged by the growing evidence on polarization in jobs and wages (Spitz-Oener, 2006; Goos and Manning, 2007; Autor and Dorn, 2009, 2013; Oesch and Rodriguez, 2011; Goos *et al.*, 2014; Bogliacino and Lucchese, 2015; Cirillo, 2016; Eurofound, 2016; Fernández-Macías and Hurley, 2016). The new approach—*routine-biased technological change* (RBTC) has focused on workers' *tasks*, arguing that computerization enhances the possibility of automating tasks characterized by a high degree of routineness (Autor *et al.*, 2003; Autor and Dorn, 2013). Routineness does not apply only to low-qualified (manual) labor processes but also to cognitive tasks (carried out mainly by managers and professionals). While non-routine cognitive tasks are likely to be complementary with digital technologies, cognitive routine tasks (typical of clerical and administrative jobs) are widely vulnerable to automation (Autor *et al.*, 2006). However, RBTC models do not provide clear indications of the net effects of digitalization on employment. While routine tasks are increasingly digitalized, new more creative and non-routinary tasks tend to emerge, in which labor can continue to hold a comparative advantage with respect to ICTs (Acemoglu and Restrepo, 2018). When digitalization and innovation are set in the context of international production based on Global Value Chains, the resulting effects on tasks and jobs appear to be increasingly complex (Marcolin *et al.*, 2016).

Instead of following these approaches, we frame the relationship between digitalization and employment in the context of the long-standing debate on the effects of technology on jobs rooted in the Schumpeterian and evolutionary tradition (Freeman and Soete, 1987; Vivarelli, 1995; Vivarelli and Pianta, 2000; Dosi and Mohnen, 2019). A large number of contributions have explored the role of technology in affecting the quantity and quality of jobs at the firm, sectoral, and country levels (for reviews, see Pianta, 2005, 2018; Vivarelli, 2014; Calvino and Virgillito, 2018). The main findings of this literature suggest that product innovation tends to have a positive employment impact in firms and industries and at the macroeconomic level. Process innovation can improve firms' performance, but their job increases may be "stolen" from the employment loss of non-innovating firms, with modest or no net job creation. Technological unemployment can be found at the level of industries or the total economy when innovations in processes dominate, reducing jobs faster than the creation of new jobs allowed by the expansion of demand (Pianta, 2018).[2]

Moreover, the offshoring of domestic production has been found to have parallel effects to technology in the reduction of jobs for manual workers in European industries (Bramucci *et al.*, 2017). The connection between the technological and organizational changes in shaping employment outcomes has also been investigated, finding that European manufacturing firms experienced the worst job losses when process and organizational innovations are combined (Evangelista and Vezzani, 2012). As to the skill composition, a move beyond skill-biased views has emerged with the use of International Standard Classification of Occupation (ISCO) data on occupational groups where the hierarchies among occupations—in terms of educational levels, task content, and wages—are more visible (Hollanders and ter Weel, 2002; Oesch and Rodriguez Menés, 2011; Cirillo, 2016, 2017; Cirillo *et al.*, 2018). Breemersch *et al.* (2019) investigate employment polarization in the manufacturing industries of 19 European countries by ranking ISCO occupations in high-, medium-, and low-paying job groups; they find that ICT adoption explains one-third of employment polarization within industries, while the intensity of research and development (hereafter R&D), offshoring, and import competition from China have more

2 These relationships between different types of innovation and employment are found also in the overview by Dosi and Mohnen (2019) of several recent contributions that investigate a large set of countries with a variety of methodologies; see in particular Breemersch *et al.* (2019) and Calvino (2019).

limited effects. These studies have shown the polarization of occupational groups in Europe and the different impact that technological change may have.

Building on this perspective, this article combines an effort to identify the relevant dimensions of digitalization in industries with attention to broader changes in economic structures, labor markets, educational levels, innovation in products and processes, and offshoring patterns. Moreover, we investigate how the expansion of digital activities can alter the type of jobs available by looking at the association with different occupational groups.

3. Data and descriptive evidence

3.1 Data

We use industry-level data from the SID developed at the University of Urbino (Pianta *et al.*, 2021). We use data on 6 major European economies—Germany, France, Italy, Spain, the Netherlands, and the UK—18 manufacturing sectors (Classes 10-33 of the Nomenclature of Economic Activities-NACE rev.2) and 23 service sectors (Classes 45-82 of NACE rev.2), focusing on the years 2009–2014—the period after the financial crisis of 2008, when the recovery of European economies offers a relevant opportunity to investigate the role played by digital technologies. The selection of countries, which represent more than 75% of the total European Union (EU)28's gross domestic product and of the 41 sectors (see Table A1 in the Appendix), is made to ensure the relevance and consistency of data used.[3] The SID combines information on employment and level of education (from the EU Labor Force Survey [LFS] and the OECD Structural Analysis database), innovation efforts (Community Innovation Surveys), digital investment (EU KLEMS, Timmer *et al.* 2015; Jäger, 2017), digital inputs and offshoring (World Input-Output Database), and demand and labor compensation (the OECD Structural Analysis database). Table A2 in the Appendix provides a description of the variables used in this article and how they have been constructed.

As for digitalization measures, we build on McKinsey Global Institute (2015) and Calvino *et al.* (2018) and identify two robust indicators of expansion of digital activities, considering also the availability and robustness of data.[4] First, we consider the share of intermediate consumption of ICT goods and services in total industries' intermediate consumption (i.e., *digital consumption*), using data from the World Input–Output Table (WIOD). The numerator of the indicator is calculated as the total intermediate purchases of sector i from ICT producing sectors[5] (k) (manufacture of computer, electronic and optical products; telecommunications; computer programming, consultancy, and related activities).

$$\text{Digital consumption}^{K}{}_{ijt} = \text{Intermediate consumption}^{K}{}_{ijt} / \text{Total intermediate consumption}_{ijt}$$
$$k \in \{\text{ICT producing sectors}: \ \text{C26}, \ \text{J61}, \ \text{J62}-\text{J63}\} \quad (1)$$

where i stands for the industry, j for the country, t for the time, and k for ICT producing sectors; in order to reduce dimensionality, we summed up purchases of ICT goods and ICT services.

The second indicator is total investment in ICTs per employee (i.e., digital investments),[6] defined as investment in tangible and intangible ICT assets, including computer hardware,

3 The Sectoral Innovation Database does not include agricultural, mining, utilities, construction, and public sectors as they are characterized by specific economic and technological activities, very distant from those of manufacturing and services. Previous work that used the Sectoral Innovation Database include Bogliacino and Pianta (2010), Bogliacino *et al.* (2013), Guarascio *et al.* (2015), Cirillo (2016, 2017), Bramucci *et al.* (2017), and Cirillo *et al.* (2018).

4 Data constraints limit the scope for more comprehensive measures of digitalization. We selected our indicators after an extensive examination of a wide range of ICT indicators collected by the Eurostat ICT Business Survey; many other indicators of digitalization have important problems (a large number of missing data; industry breakdowns change over time and countries; data are based on rough dichotomic yes/no questions).

5 Differently from Calvino *et al.* (2018), we also consider telecommunications services.

6 ICT investment data were drawn from EU KLEMS; in order to match the sectoral breakdown available in the WIOD and the LFS (Nace Rev. 2), in some cases when ICT investment data were available only for one-digit classes, the same value was assigned to all its two-digit sub-classes.

telecommunication equipment, software, and databases, all drawn from EUKLEMS.

$$\text{Digital investment}^{k}_{ijt} = \text{Gross fixed capital formation}^{k}_{ijt} / \text{Total number of employees}_{ijt}$$
$$k \in \{\text{Computer hardware, communication equipment, software and databases}\} \quad (2)$$

where *i* stands for the industry, *j* for country, and *t* for time.

In order to consider the role of offshoring, we follow Guarascio *et al.* (2015) and construct an indicator computed as the share of intermediate inputs inflowing from foreign low-tech industries in industries' in total intermediate inputs. Low-tech industries are defined as those included in the Revised Pavitt Classes of Scale and information-intensive and supplier-dominated industries, listed in Table A1. Previous studies have shown that this is a robust proxy of offshoring displacing domestic production (Bramucci *et al.*, 2017).

$$\text{Offshoring}^{k}_{ijt} = \text{Imported intermediate inputs}^{k}_{ijt} / \text{Total intermediate inputs}_{ijt}$$
$$k \in \{\text{Low} - \text{tech foreign industries(Scale intensive and Supplier dominated)}\} \quad (3)$$

The SID allows us to control for a rich set of industry-level variables, innovation activities, demand, international fragmentation of production, and changes in the educational levels and wages (Pianta *et al.*, 2021). The list of variables used in the empirical analysis is listed in Table A2 in the Appendix.

3.2 The investigation of skills

Aggregate data on employment hide important differences in the dynamics of the various components of the labor force. Labor markets have been undergoing major structural transformations in the level and composition of employment, with important roles played by the expansion of digital activities, the broader process of technological change, and globalization. It is therefore crucial to account for such drivers of change when investigating the shift in demand for different skill groups.

For this purpose, we rely on the classification of occupations provided by the ISCO, widely adopted in empirical research.[7] The ISCO classification reflects the nature of the tasks performed and the skill content of labor activities. Our main data source for employment is the EU LFS for the 2009–2014 period. The EU LFS contains data on employment status, education level, and ISCO at one-digit codes and two-digit NACE revision 2 industry codes.

Following Cirillo (2017) and Cirillo *et al.* (2018), we define four main macro-occupational groups—managers, clerks, craft, and manual workers—by aggregating ISCO one-digit classes[8] in the way shown in Table 1.

The advantage of studying occupational grouping is that it summarizes the hierarchical position of workers, the task content of jobs, the levels of education, and wage differences. In Figure A1 (in the Appendix), we report wages by occupation—from the highest-paid managers and professionals to the lowest-paid workers in elementary occupations, documenting a broad hierarchy among occupations.

Figure 1 shows the distinct patterns of change among these four occupational groups and the process of polarization under way in recent years. Job gains are concentrated in managers and manual workers, while the middle-skill groups of clerks and craft workers have stagnant employment. The different polarization patterns in manufacturing and services are also documented. Figure A2 in the Appendix reports data for the individual countries considered.

7 The ISCO classification has been adopted by the studies of Hollanders and ter Weel, 2002; Oesch and Rodriguez Menés, 2011). We do not consider the ISCO class of Armed forces.

8 A revision of the International Standard Classification of Occupations (ISCO) took place in 2011, when ISCO-88 was succeeded by ISCO-08, resulting in a break in the occupational series; Germany reassigned some ISCO occupations in 2012 (Eurofound, 2017). To achieve consistency in data for the period of our analysis, we opt for the updated classification ISCO-08 and estimate 2009 absolute values of each occupational group (managers, clerks, craft workers, and manual workers) on the basis of the ratio in 2011 for all countries except for Germany, where the ratio in 2012 has been used.

Table 1. The occupational groups

Occupational groups	ISCO one-digit classes
Managers	Managers, senior officials, and legislators Professionals Technicians and associate professionals
Clerks	Clerks Service and sales workers
Craft workers	Skilled agricultural and fishery workers Craft and related trade workers
Manual workers	Plant and machine operators and assemblers Elementary occupations

Source: Cirillo (2017).

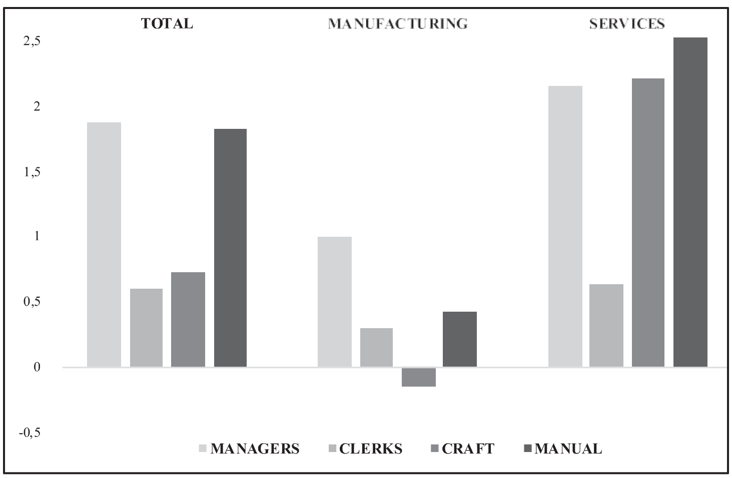

Figure 1. Employment change in occupational groups
Source: Authors' elaboration based on EU LFS.
Note: Rate of change of employment was calculated for each occupational group and by macro-sector (manufacturing and services), over the 2012–2017 period. The sample includes all six countries (DE, ES, FR, IT, NL, UK).

3.3 Descriptive evidence

In this section, we provide some descriptive evidence on the level of digital activities and on employment patterns across sectors, countries, and occupational groups. In order to keep the sectoral analysis of the data simple and insightful, industries are grouped according to the Revised Pavitt taxonomy proposed by Bogliacino and Pianta (2010): Science-based (SB), specialized suppliers (SS), scale and information-intensive (SI), and supplier-dominated (SD), that is reported in Table A1 in the Appendix. Figure A3 in the Appendix shows the occupational structure of the workforce in each Pavitt class, documenting the strong existing differences.

Table 2 reports summary statistics for the key variables used in the analysis, grouping industries in the Revised Pavitt classes. A clear hierarchy among such groups emerges for digital and technological variables, as well as in the employment change, with significant differences.[9]

The main patterns emerging from Table 2 are the following:

9 Analysis of variance confirms that there is more variation between than within Pavitt classes. It reports the presence of statistically significant differences across at least two Pavitt classes in terms of digital and innovation patterns. The multiple-comparison test (Bonferroni, Scheffe, and Šidak test) finds significant differences in the mean values of Pavitt classes in four out of six pairwise combinations (SB vs. SS, SB vs. SD, SII vs. SD, and SB vs. SII).

Table 2. Summary statistics

Pavitt classes	ICT inv. per emp. (000€)	ICT consumption (%)	Product inno. only (%)	Process inno. only (%)	Offshoring low-tech (%)	Δ Total Employees (%)	ΔManagers (%)	ΔClerks (%)	ΔCraft workers (%)	ΔManual workers (%)
Science based	8.0	25.1	19.1	6.5	6.1	0.5	0.3	−1.0	−2.3	2.4
Specalised suppliers	1.7	6.3	14.2	8.4	7.0	0.7	0.9	0.7	5.2	3.5
Scale and information intensive	3.3	6.2	12.0	10.3	11.1	−1.2	−0.6	−2.3	−0.3	0.7
Supplier dominated	1.1	4.4	6.9	6.7	8.6	0.4	0.7	0.1	1.3	1.9

Sources: Authors' elaboration based on the SID (Sectoral Innovation Database). The description of variables is in Table A2 in the Appendix. Table reports average values by revisited Pavitt industry groups weighted for the size of the industry. The sample corresponds to the one used in the econometric analysis.

(i) SB industries are at the core of digital transformation in all six countries, as key sectors with high ICT content are included in this group (manufacture of computer, electronic and optical products; telecommunications; computer programming, consultancy, and related activities). They show the highest levels of both digital investment and use of digital inputs;
(ii) SS industries are characterized by a medium use of digital intermediate inputs (in particular for services: management consultancy, engineering, marketing, other professional services) and by relatively low ICT investment.
(iii) SI industries are characterized by medium levels of digital investments (mostly driven by financial services and media sectors) and limited use of intermediate digital inputs;
(iv) SD industries show the lowest levels of digitalization (except for postal services associated with a high share of digital inputs).

What is the relationship between our two proxies of digitalization and changes in employment? Figures 2 and 3 show these relationships in the period 2009–2014; SB industries are excluded from these figures due to the magnitude of their ICT indicators. First, we observe the poor employment performances experienced by the majority of industry groups in the period taken into account, a reflection of the long European stagnation. Second, two distinct patterns emerge in the relationship between digitalization and employment; Figure 2 shows a negative relationship between the level of investment in ICT and employment change. Figure 3 shows a weak positive association between the use of ICT intermediate inputs and the capacity of industries to create new jobs or to limit employment losses. Third, we observe that job losses are unevenly spread; geographically, they are more pronounced in Southern EU countries (Italy and Spain); employment falls in SI industries including financial sectors and media, which are undergoing a major restructuring. The same employment pattern is found for telecommunications, which has the highest digital intensity and is part of the SB group. Conversely, other highly digital sectors—such as IT services and research and development—show high employment growth rates.

4. The model and empirical strategies

Our econometric exercise has not the ambition to test for the existence of causal relationships between the levels of ICT investment and digital consumption (and more broadly all the variables used as regressors) on the one hand and employment on the other. It rather aims at identifying how the different patterns of diffusion of digital technologies are associated with employment changes in European industries, controlling for different trajectories of technological change, the role of offshoring, demand, and university education; we also focus on the structural diversities across industries—including those between manufacturing and services—and on the diversity of changes across occupational groups. Building on the conceptual framework discussed above, the employment equation can be formally written as follows:

$$\Delta EMPE_{i,t} = \beta_0 + \beta_1 \Delta VA_{i,t-1} + \beta_2 \Delta W_{i,t-1} + \beta_3 \Delta EDU_{i,t} + \beta_4 DigINV_{i,t} + \beta_5 DigCONS_{i,t} + \beta_6 PROD_{i,t-1} + B_7 PROC_{i,t-1} + \beta_9 Offsh_{i,t} + \epsilon_{i,t} \quad (4)$$

where i and t are indices for industry and time, respectively. $\Delta EMPE$ is the rate of change of the number of employees; lagged ΔVA is the rate of growth of demand proxied by value added; lagged ΔW is the rate of growth of the labor compensation per employee; ΔEDU measures the growth rate of university graduates; $DigINV$ and $DigCONS$ denote the average ICT investments per employee and the average share of digital inputs over the period; lagged $PROD$ and $PROC$ denote the introduction new products and processes, respectively; finally, $Offsh$ represents offshoring to low-tech industries, while ϵ is the error term. More information on variables and lags is provided in the Appendix (Table A2).

We adopt the following identification strategy. First, we include South dummy in all specifications to control for geographical differences—South vs. Core—as job losses were more pronounced in the former. Second, next to our rich set of control variables, we also control

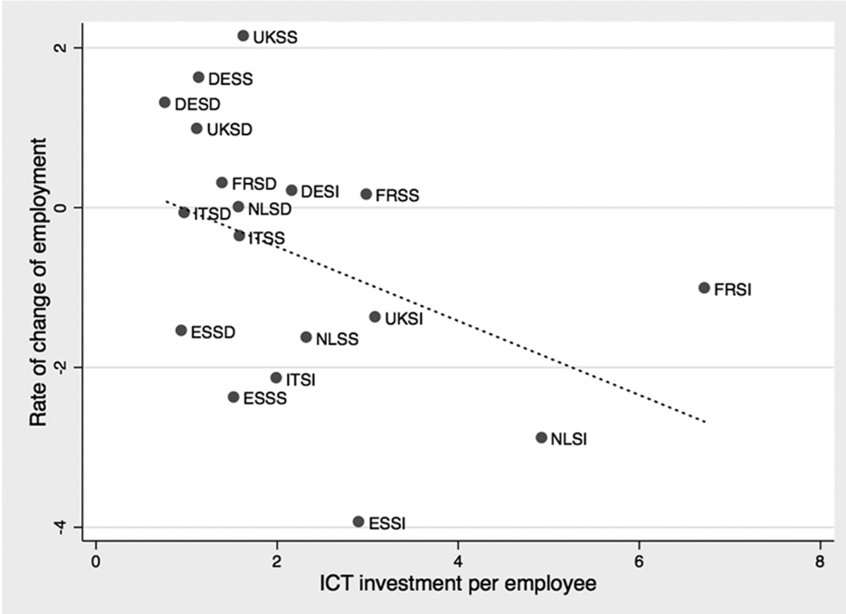

Figure 2. Rate of change of employment and digital investments
Sources: Authors' elaboration based on the SID (Sectoral Innovation Database), 2009–2014.
Notes: The figure plots rate of change of employment against average annual ICT investment per employee (thousand euros) over the 2009–2014 period. Observations refer to the country-Pavitt averages, and the sample corresponds to the one used in the econometric analysis. Science-based industries are excluded from the figure due to the magnitude of their ICT indicators.

for the structural differences—between the manufacturing and service sectors—with manufacturing dummy. Third, to reduce the risk of simultaneity-related endogeneity bias, we introduce a time lag between our dependent variable and most of our independent variables, whereas ICT variables are considered as mean values over the entire period; Fourth, as it may not be plausible to assume that every observation should be treated equally—considering that industry data are typically grouped data of unequal size—we employ weighted least squares estimator, using the number of employees as weights. Otherwise, the consistency of the estimator might be affected by the asymmetric information provided by industry data (e.g., sectors of small size and modest economic significance contribute equally to large sectors). Finally, estimated standard errors were adjusted for heteroskedasticity.

Building on the conceptual framework proposed in Section 2—rooted in Schumpeterian and evolutionary approaches—and on previous empirical findings (Bogliacino and Pianta, 2010; Cirillo, 2017; Cirillo *et al.*, 2018), we expect that the following relationships may emerge: the growth of industries' demand promotes job expansion; the "neoclassical" negative relationship is expected between wages and employment; on the supply side, a greater share of employees with university degree favors faster employment growth as industries with higher levels of knowledge embodied in workers tend to be more dynamic; large digital investments per employee are expected to be associated to restructuring processes and labor-saving effects; conversely, higher digital inputs can contribute to improvement in products and may be associated with faster employment dynamics; as shown by a large literature, we expect technological and cost-competitiveness strategies to have contrasting relationships with employment; finally, an increase in offshoring is expected to reduce employment opportunities.

Furthermore, we are interested in exploring structural differences in the relationships. Thus, we estimate equation (4) separately for manufacturing and services.

In order to test the hypothesis of diversity in the relationships affecting occupations, we estimate the following set of equations (5–8) for each occupational group (managers, clerks, craft,

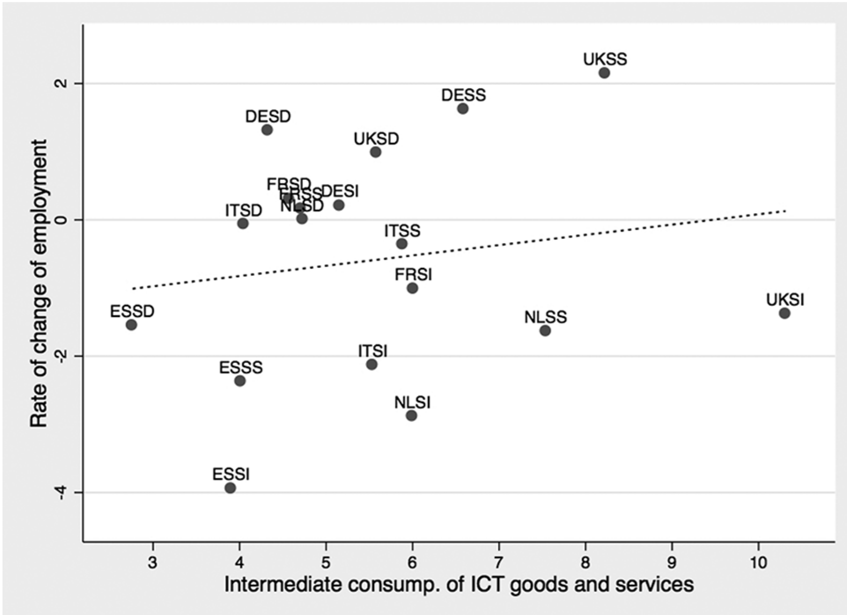

Figure 3. Rate of change of employment and digital consumption
Sources: Authors' elaboration based on the SID (Sectoral Innovation Database), 2009–2014.
Notes: Figure plots rate of change of employment against the average annual share of intermediate ICT goods and services consumption over the 2009–2014 period. Observations refer to the country-Pavitt averages, and the sample corresponds to the one used in the econometric analysis.Science-based industries are excluded from the figure due to the magnitude of their ICT indicators.

and manual workers):[10]

$$\begin{aligned}\Delta Manager_{i,t} = {} & \beta_0 + \beta_1 \Delta VA_{i,t-1} + \beta_2 \Delta W_{i,t-1} + \beta_3 \Delta EDU_{i,t} + \beta_4 DigINV_{i,t} \\ & + \beta_5 DigCONS_{i,t} + \beta_6 PROD_{i,t-1} + B_7 PROC_{i,t-1} + \beta_9 Offsh_{i,t} + \Delta \in_{i,t}\end{aligned} \tag{5}$$

$$\begin{aligned}\Delta Clerks_{i,t} = {} & \beta_0 + \beta_1 \Delta VA_{i,t-1} + \beta_2 \Delta W_{i,t-1} + \beta_3 \Delta EDU_{i,t} + \beta_4 DigINV_{i,t} + \beta_5 DigCONS_{i,t} \\ & + \beta_6 PROD_{i,t-1} + B_7 PROC_{i,t-1} + \beta_9 Offsh_{i,t} + \Delta \in_{i,t}\end{aligned} \tag{6}$$

$$\begin{aligned}\Delta Craft\ workers_{i,t} = {} & \beta_0 + \beta_1 \Delta VA_{i,t-1} + \beta_2 \Delta W_{i,t-1} + \beta_3 \Delta EDU_{i,t} + \beta_4 DigINV_{i,t} + \beta_5 DigCONS_{i,t} \\ & + \beta_6 PROD_{i,t-1} + B_7 PROC_{i,t-1} + \beta_9 Offsh_{i,t} + \Delta \in_{i,t}\end{aligned} \tag{7}$$

$$\begin{aligned}\Delta Manual\ workers_{i,t} = {} & \beta_0 + \beta_1 \Delta VA_{i,t-1} + \beta_2 \Delta W_{i,t-1} + \beta_3 \Delta EDU_{i,t} + \beta_4 DigINV_{i,t} \\ & + \beta_5 DigCONS_{i,t} + \beta_6 PROD_{i,t-1} + B_7 PROC_{i,t-1} - \beta_9 Offsh_{i,t} + \Delta \in_{i,t}\end{aligned} \tag{8}$$

Building on this approach we can therefore shed new light on:

10 Many studies investigating employment change relied on a translog cost function (see Berman *et al.*, 1994; Machin and Van Reenen, 1998). We adapt this approach considering rates of change rather than shares of total employment.

Table 3. Regression results for the rate of change of employment

	(1)	(2)	(3)	(4)
ΔValue added	0.316***	0.303***	0.223***	0.209***
	(0.0566)	(0.0581)	(0.0591)	(0.0578)
ΔWages	−0.173*	−0.191**	−0.125	−0.127
	(0.0955)	(0.0919)	(0.0855)	(0.0841)
ΔUniversity graduates	0.131***	0.127***	0.128***	0.123***
	(0.0345)	(0.0337)	(0.0311)	(0.0312)
ICT investment	−0.129***	−0.132***	−0.125***	−0.136***
	(0.0293)	(0.0288)	(0.0278)	(0.0277)
ICT int. consumption	0.0369***	0.0308***	0.0286**	0.0279**
	(0.0120)	(0.0115)	(0.0118)	(0.0114)
Product innovation	0.0246*	0.0290**	0.0186	0.0375**
	(0.0132)	(0.0137)	(0.0130)	(0.0148)
Process innovation	−0.0418	−0.0410	−0.0193	0.000232
	(0.0342)	(0.0348)	(0.0350)	(0.0362)
Offshoring low-tech		−0.0458*	−0.0718***	−0.0387
		(0.0261)	(0.0273)	(0.0280)
South dummy			−1.347***	−1.202***
			(0.374)	(0.368)
Manufacturing dummy				−0.879***
				(0.323)
Constant	−0.177	0.255	0.696	0.329
	(0.526)	(0.517)	(0.538)	(0.536)
Observations	214	214	214	214
R^2	0.393	0.406	0.473	0.493

Weighted least square estimation. Weights are the number of employees. The dependent variable is the average annual rate of change of employment. South dummy is equal to 1 if the country is Italy or Spain, zero otherwise. Manufacturing dummy equals 1 for manufacturing industry (10–33 NACE Rev.2), zero otherwise. Robust standard errors are reported in parentheses, with significance levels
***$P < 0.01$,
**$P < 0.05$,
*$P < 0.1$.

(i) The structural change of the economy, namely the expansion or contraction of industries and the long-term shift from manufacturing to services.
(ii) The dominance of technological trajectories based on either a search for new products and services with a potential job-creating effect or the search for new processes relying on a cost-competitiveness strategy.
(iii) The distinct ways in which digitalization is associated with employment: on the one hand, large ICT investment can reshape production processes favoring restructuring and job cuts, similarly to the process innovation; on the other hand, the diffusion of ICTs across industries, in the form of intermediate inputs that improve products and services and promote the expansion of jobs.

5. Results

Table 3 reports the estimation results of equation (4) highlighting the factors affecting total employment. In Table 4, we split the sample between manufacturing and services. Finally, the estimation results of equations (5–8) for each occupational group are reported in Table 5.

Results in Table 3 largely confirm the relationships we anticipated in presenting the model in Section 4. In specifications (3) and (4), we introduced dummy variables for Southern European countries (Italy and Spain) and for manufacturing industries, in order to control for the observed differences in their employment patterns.

Table 4. Regression results for the rate of change of employment in manufacturing and services

	Manufacturing		Services	
	(1)	(2)	(3)	(4)
ΔValue added	0.430***	0.346***	0.108	0.0693
	(0.0643)	(0.0714)	(0.0838)	(0.0809)
ΔWages	−0.208	−0.179	−0.149	−0.0956
	(0.131)	(0.122)	(0.117)	(0.110)
ΔUniversity graduates	0.0222	0.0417	0.222***	0.203***
	(0.0284)	(0.0321)	(0.0587)	(0.0568)
ICT investment	−0.219***	−0.214***	−0.111***	−0.101***
	(0.0342)	(0.0324)	(0.0345)	(0.0309)
ICT int. consum.	0.0179	0.0174	0.0465***	0.0415***
	(0.0207)	(0.0179)	(0.0156)	(0.0152)
Product innovation	0.0542***	0.0447***	0.0522	0.0303
	(0.0126)	(0.0117)	(0.0402)	(0.0372)
Process innovation	0.0186	0.0406	−0.0209	−0.0246
	(0.0360)	(0.0340)	(0.0517)	(0.0515)
Offshoring low-tech	0.0183	−0.0108	−0.0659	−0.0986*
	(0.0227)	(0.0250)	(0.0489)	(0.0522)
South dummy		−1.166**		−1.070**
		(0.481)		(0.427)
Constant	−1.235*	−0.751	−0.497	0.269
	(0.711)	(0.688)	(0.917)	(0.987)
Observations	105	105	109	109
R^2	0.572	0.602	0.402	0.456

Weighted least square estimation. Weights are the number of employees. The dependent variable is the average annual rate of change of employment. South dummy is equal to 1 if the country is Italy or Spain, zero otherwise. Columns 1–4 distinguish between manufacturing and service industries. Robust standard errors are reported in parentheses, with significance levels
***$P < 0.01$,
**$P < 0.05$,
*$P < 0.1$.

In all four specifications of the model, job creation goes hand in hand with the expansion of value added with positive and significant coefficients; this reflects the relevance of structural change and demand in shaping the growth opportunities of industries.

A “neoclassical” negative and significant relationship between job growth and wages is found in the first two specifications; when the South dummy is included, the significance is lost due to the labor market specificities of Italy and Spain.

The importance of human capital, measured by the growth of university graduates, is shown by the positive and significant coefficients in all estimations.

As expected, the two types of digital activities investigated in our study have contrasting associations with employment change; digital investment shows a negative and significant relationship with total jobs, as they are likely to contribute to restructuring processes in industries. Conversely, the consumption of digital inputs has a positive and significant relationship with job creation; this is likely to be the result of the improved quality of products and services integrating digital inputs.

Offshoring to low-tech industries has a significant negative relation with domestic jobs; as offshoring is mainly affecting manufacturing, when a dummy for manufacturing industries is included, the statistical significance is lost.

The distinct effect of product and process innovation on employment also emerge; the presence of new products and services has a positive association with job creation; the introduction of process innovations is not significant as they are likely to affect industries in a way similar to the variables on ICT investment and offshoring.

Overall, results appear to be robust to the different specifications. We replicated the analysis by excluding from the sample the most digitalized sectors (ICT services and manufacturing), and the coefficients on our two digital indicators are significant.

Table 5. Regression results for the rate of change of employment in occupational groups

	Managers (1)	Clerks (2)	Craft workers (3)	Manual workers (4)
ΔValue added	0.163**	0.173	0.224	−0.0979
	(0.0731)	(0.113)	(0.137)	(0.151)
ΔWages	−0.0234	0.214	0.0802	−0.147
	(0.0932)	(0.141)	(0.171)	(0.148)
ΔUniversity graduates	0.624***	0.486***	0.367***	0.444***
	(0.0520)	(0.0622)	(0.0576)	(0.0838)
ICT investment	−0.0270	−0.204***	0.0479	−0.126
	(0.0297)	(0.0580)	(0.124)	(0.120)
ICT int. consumption	0.0326*	0.0411	−0.120**	−0.0611
	(0.0177)	(0.0300)	(0.0539)	(0.0648)
Product innovation	0.0449**	0.0309	−0.0149	0.0928**
	(0.0190)	(0.0295)	(0.0332)	(0.0393)
Process innovation	0.0789*	0.0399	−0.0378	0.184***
	(0.0427)	(0.0508)	(0.0612)	(0.0700)
Offshoring low-tech	−0.0767**	−0.0654	−0.166***	−0.0660
	(0.0329)	(0.0639)	(0.0579)	(0.0523)
South	−0.779*	−1.303*	−3.955***	−1.933**
	(0.468)	(0.711)	(0.834)	(0.748)
Manufacturing	0.488	0.103	−0.440	−1.755**
	(0.497)	(0.749)	(0.969)	(0.843)
Constant	−2.406***	−2.087*	3.139**	−1.841
	(0.667)	(1.139)	(1.502)	(1.142)
Observations	221	221	193	203
R^2	0.599	0.439	0.407	0.292

Weighted least square estimation. Weights are the number of managers, clerks, craft workers, and manual workers, respectively. South dummy is equal to 1 if the country is Italy or Spain, zero otherwise. Manufacturing dummy equals 1 for manufacturing industry (10–33 Nace Rev.2), zero otherwise. Robust standard errors are reported in parentheses, significance levels
***$P < 0.01$,
**$P < 0.05$,
*$P < 0.1$.

A major novelty of these findings is the coexistence of significant relationships for all the variables we have considered. Employment in European industries is increasing in the sectors characterized by higher educational levels, greater digital contents (in terms of intermediate inputs), and greater innovation efforts (introduction of new products). All these appear to have parallel effects on the job creation potential of digital and technological change, and it is remarkable that they capture distinct aspects that cannot be reduced to a generic ICT-based technological upgrading. In contrast, employment in European industries is negatively related to the intensity of digital investment and offshoring of low-tech activities. In addition, demand clearly matters, as value-added growth allows employment creation, while industries with greater wage growth show lower employment dynamics.

Are the manufacturing and service industries characterized by the same set of relationships? Table 4 reports the regression results of equation (4) separately estimated on manufacturing and service industries. Differences prevail over commonalities, with significant specificities in the case of Southern European countries. Employment change in manufacturing industries is positively associated with value-added growth and product innovation and negatively correlated to digital investment. In contrast, employment change in services is positively associated with intermediate digital inputs and growth of university graduates and negatively linked to digital investment and offshoring. What emerges is a pattern of change in manufacturing where job-creating effects are driven by the combination of technological change in new products and demand-pull factors, while labor-saving restructuring strategies mainly take place through digital investment. Conversely, the job-friendly expansion of services is driven by high human capital and high digital inputs in industries; labor-saving restructuring mainly emerges, again, through digital investment.

Finally, we investigate the four occupational groups (equations 5–8) aiming at identifying the persistence and diversity of relationships; results are shown in Table 5. Digitalization and technological change affect occupational groups in distinct ways, although a larger share of university graduates is a positive and significant factor for all of them.

Demand for managers is greater in industries characterized by a higher relevance of intermediate digital inputs, innovation efforts (both product and process), and demand; it is lower in industries that rely on offshoring. Employment change for clerks is mainly driven by the negative role of digital investment. For craft workers, job losses are associated with greater use of intermediate digital inputs and to the relevance of offshoring. Finally, for manual workers innovation efforts (product and process innovations) are positively associated with job creation. The negative relation between wage levels and job creation is never significant, as we consider here the average wage in the industry (wage data for individual occupations are not available).

Summing up the findings, we can point out that the knowledge embodied in employees—documented by industries' share of graduates—plays a positive and significant role in job creation in all four occupational groups, while digitalization has a differentiated impact. A greater use of digital inputs is associated with more managerial jobs and with job losses for craft workers; digital capital deepening is associated with job losses for clerks; manual jobs appear to be unaffected by digitalization and are rather associated with technological innovations. Offshoring emerges in some cases as a contributing factor in job losses. The South dummy—as in all previous tests—is always negative and significant, showing that Italy and Spain lag behind in their employment performances.

6. Conclusions

From our investigation, a number of novelties have emerged, integrating the results obtained by previous studies that have already explored the different dimensions and complex effects of digitalization (Brynjolfsson and McAfee, 2014; Marcolin *et al*., 2016; Calvino *et al*., 2018; Dosi and Mohnen, 2019).

First, we have provided original evidence on the diversity of the trajectories of expansion of digital activities and on their contrasting associations with total employment. Rather than thinking of digitalization as a one-directional process, where "given" technologies shape economic change, employment, skills, and wages, we have shown that two main distinct trajectories are at work. On the one hand, when industries acquire greater intermediate inputs from digital sectors, they are able to improve the quality and technological content of their goods and services, increasing their economic performances and jobs. On the other hand, when digital investments per employee increase, novel production systems are introduced, replacing labor in order to reduce costs, sometimes with extensive processes of restructuring.

While there is a complementarity—up to a point—between firms' ability to use more digital inputs and invest more in digitalization, we have found that at the industry level the contrasting employment outcomes of the two strategies do emerge. Therefore, an important result of our study is that we should move beyond a view of digitalization as a homogenous process, considering the diversity of digitalization strategies, with their contrasting economic and employment effects.

Second, we have shown that digitalization closely interacts with changes in industry structures, demand dynamics, labor market conditions, and technological innovation in shaping employment outcomes. An important result is that the acquisition of digital inputs operates in a similar way to product innovations. Both contribute to industries' ability to achieve Schumpeterian advantages based on novel products and services incorporating advanced digital technologies. Greater digital inputs and the introduction of product innovations allow firms and industries to grow faster in terms of output and jobs. Conversely, high levels of digital investments per employee—including computer hardware and software, telecommunication equipment, and databases—appear to prevail on the effect of process innovation (a variable that is not significant in our tests on total employment), as they both allow the restructuring of production activities with greater efficiency and flexibility, and with fewer workers. It is important to note that our econometric results show that the parallel effects of technological innovation and digital activities—when they expand employment—do now overlap but rather may integrate one another, capturing different aspects of industries' strategies aiming at upgrading production capabilities.

Third, we have documented the increasing polarization of the occupational structure in European industries, clearly shown by the use of ISCO occupational groups, and we have highlighted the diversity of drivers affecting the employment expansion of managers and manual workers and the job stagnation or contraction of clerks and craft workers. In line with the descriptive evidence on polarization of occupations, we find that demand for managers is greater in industries characterized by a higher share of intermediate digital inputs and greater technological innovation, while digital investment and intermediate inputs have negative associations with middle occupations (clerks and craft workers, respectively). In addition, the industries' share of university graduates has a positive association with job creation in all four occupational groups, while other variables have emerged as significant factors in the employment change of selected occupational categories.

Finally, these results provide new insights, setting digitalization in the broader context of technological and economic change occurring in European industries after the 2008 crisis. While digitalization and its effects are a long-run process to be explored over extended time series, the period considered—2009–2014—offers significant evidence of changes occurring in employment as European economies were recovering—at a very uneven pace—from the crisis; this upswing of the business cycle appears as an appropriate phase for investigating the diffusion and impact of digital technologies.[11] Moreover, countries do differ in their ability to benefit from the opportunities of digitalization, and the employment performances in Italy and Spain are systematically lower than those of Northern European countries. Far from showing a generalized skill upgrading and an overall improvement of jobs as a result of digitalization and technological change, we found that different strategies are associated with contrasting occupational outcomes. This helps identify key drivers of the current polarization of jobs and the winners and losers in occupational groups.

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Appendix

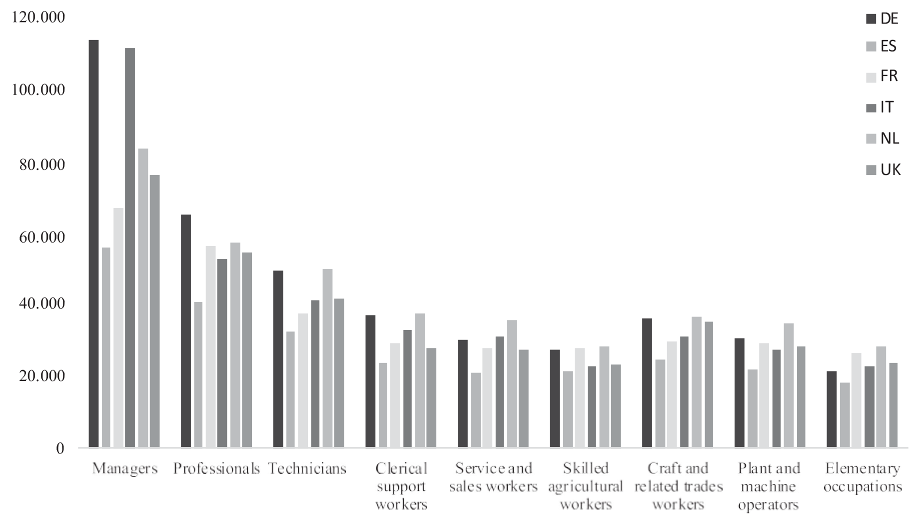

Figure A1. Gross annual earnings by ISCO one-digit occupations, 2014
Sources: Authors' elaboration based on the Structure of Earnings Survey 2014.
Notes: The bars show gross annual earnings in euros for nine major occupational groups in 2014.The sample comprises manufacturing and service industries and excludes armed forces.

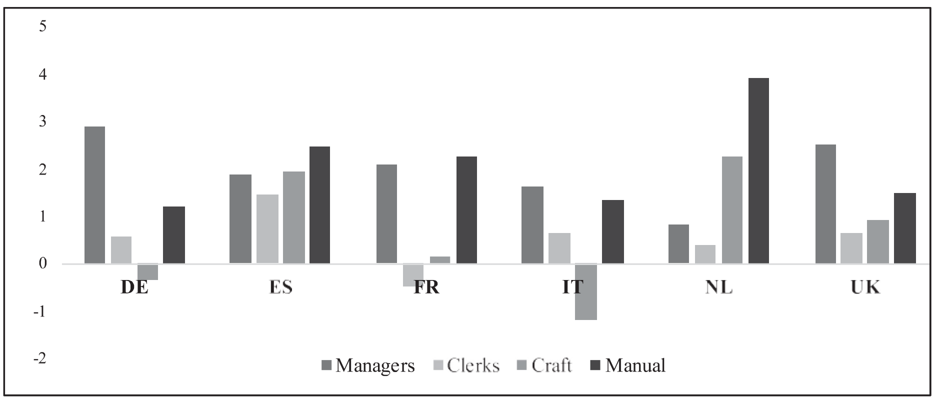

Figure A2. Rate of change of employment by occupational group
Source: Authors' elaboration based on the EU LFS.
Note: Rate of change of employment was calculated for each occupational group and by country-macro-sector (manufacturing and services), over the 2012–2017 period. The sample includes all six countries (DE, ES, FR, IT, NL, UK).

Table A1. List of sectors

Sectors (NACE Rev. 2 classification)	NACE codes	Revised Pavitt class
Manufacture of food products, beverages, and tobacco products	C10–C12	SD
Manufacture of textiles, wearing apparel, and leather products	C13–C15	SD
Manufacture of wood and products of wood and cork, except furniture	C16	SD
Manufacture of paper and paper products	C17	SI
Printing and reproduction of recorded media	C18	SI
Manufacture of chemicals and chemical products	C20	SB
Manufacture of basic pharmaceutical products and pharmaceutical preparations	C21	SB
Manufacture of rubber and plastic products	C22	SI
Manufacture of other non-metallic mineral products	C23	SI
Manufacture of basic metals	C24	SI
Manufacture of fabricated metal products, except machinery and equipment	C25	SD
Manufacture of computer, electronic, and optical products	C26	SB
Manufacture ofelectrical equipment	C27	SS
Manufacture of machinery and equipment n.e.c.	C28	SS
Manufacture of motor vehicles, trailers, and semi-trailers	C29	SI
Manufacture of other transport equipment	C30	SS
Manufacture of furniture; other manufacturing	C31–C32	SD
Repair and installation of machinery and equipment	C33	SS
Wholesale and retail trade and repair of motor vehicles and motorcycles	G45	SD
Wholesale trade, except motor vehicles and motorcycles	G46	SD
Retail trade, except motor vehicles and motorcycles	G47	SD
Land transport and transport via pipelines	H49	SD
Water transport	H50	SD
Air transport	H51	SD
Warehousing and support activities for transportation	H52	SD
Postal and courier activities	H53	SD
Accommodation and food service activities	I55–I56	SD
Publishing activities	J58	SI
Audio-visual and broadcasting activities	J59–J60	SI
Telecommunications	J61	SB
Computer programming, consultancy and related activities; information service act.	J62–J63	SB
Financial service activities, except insurance and pension funding	K64	SI
Insurance, reinsurance and pension funding, except compulsory social security	K65	SI
Activities auxiliary to financial services and insurance activities	K66	SI
Real estate activities	L68	SS
Legal and accounting activities; management consultancy activities	M69–M70	SS
Architectural and engineering activities; technical testing and analysis	M71	SS
Scientific research and development	M72	SB
Advertising and market research	M73	SS
Other professional, scientific and technical activities; veterinary activities	M74–M75	SS
Administrative and support service activities	N	SD

Revised Pavitt classes: SB: science-based; SS: specialised supplier; SI: scale and information-intensive; SD: supplier-dominated.

Table A2. Variable definition and data sources

Variable	Description	Ref. period
Value added	Value added is expressed as a compound annual growth rate. Value added in current prices was deflated by country-industry specific value-added deflators sourced from the OECD's STAN. Source: STAN	2007–2012
Labor compensation per employee	Average labor compensation per employee in the industry is expressed as a compound annual growth rate. Labor compensation in current prices is deflated by aggregate value-added deflator. Source: STAN	2007–2012
Employment	Employment is measured in terms of the number of employees and is expressed as a compound annual rate of growth rate. Source: STAN	2009–2014
Investment in ICT per employee	Investments are deflated using aggregate value-added deflator.[a] In exceptional cases—when the EU KLEMS reports investment data only at one-digit industry level (e.g., one-digit sector K "Finance, Insurance and Auxiliary activities")—we assign the same value to its two-digits counterparts (e.g., two-digit sectors K64 "Financial Service Activities," K65 "Insurance," K66 "Auxiliary fin. Activities"), in order to match the industry classification available in Table A1. Source: EU KLEMS	2009–2014
Intermediate consum. of ICT goods and services	The methodology for the construction of this variable is explained in the text. Source: WIOD	2009–2014
Low-tech offshoring	The methodology for the construction of this variable is explained in the text. Source: WIOD	2009–2014
Firms introducing new processes only	Share of firms that implemented a new or significantly improved production or delivery method only in the observed period. Source: EUROSTAT, Community Innovation Survey	2008–2010
Firms introducing new products only	Share of firms that significantly improved their goods and services in the observed period. Source: EUROSTAT, Community Innovation Survey	2008–2010
University graduates	This variable is first calculated as the sum of employees having at least a bachelor's degree (ISCED 6, ISCED 7, ISCED 8) and then expressed as a compound annual growth rate. Source: EU LFS	2009–2014
Managers	This variable is firstly calculated as the sum of employees in ISCO1, ISCO2, ISCO3 occupations and then expressed as a compound annual growth rate. Source: EU LFS	2009–2014
Clerks	This variable is firstly calculated as the sum of employees in ISCO4 and ISCO5 occupations and then expressed as a compound annual growth rate. Source: EU LFS	2009–2014
Craft workers	This variable is firstly calculated as the sum of employees in ISCO6 and ISCO7 occupations and then expressed as a compound annual growth rate. Source: EU LFS	2009–2014
Manual workers	This variable is firstly calculated as the sum of employees in ISCO8 and ISCO9 occupations and then expressed as a compound annual growth rate. Source: EU LFS	2009–2014

All series are expressed in constant terms using 2000 as a base year. For the UK variables initially reported in pounds, after being corrected for inflation, we convert to euros using the exchange rate expressed in PPP provided by Stapel *et al.* (2004: 5).

[a]There are substantial disparities in the measurement of ICT price indices across countries. In order to avoid distortions, we opted for the aggregate value-added deflator instead of ICT deflator. In this way, we potentially underestimate the growth in real ICT investment; however, we do not expect significant changes in the ranking of industries in terms of ICT investment to occur.

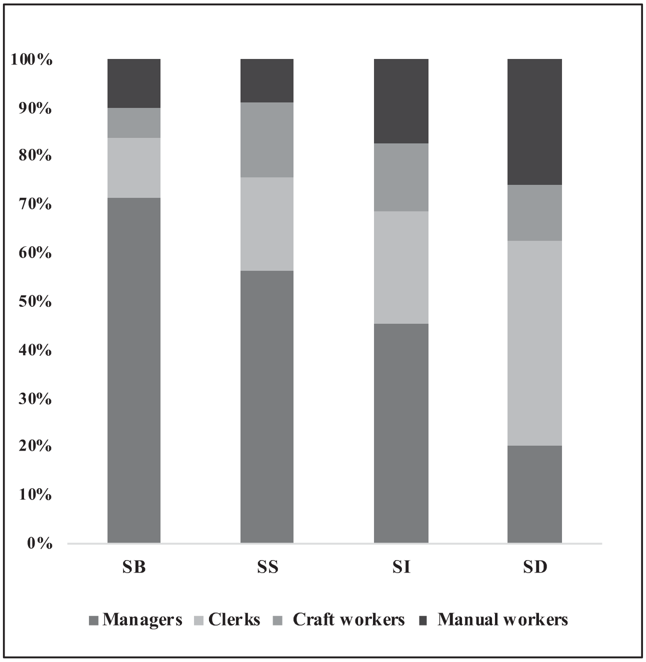

Figure A3. Occupational structure by Revised Pavitt industry groups, 2014
Sources: Authors' elaboration based on the SID (Sectoral Innovation Database), 2014.
Notes: Figure plots the occupational structure by revisited Pavitt industry groups in 2014.The sample corresponds to the one used in the econometric analysis.